LWD POROSITY PREDICTION FOR WELL PLACEMENT USING NEURAL NETWORK

BY

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NOMENCLATURE

AAPE	=	Average Absolute Percent Relative Error (Ea).
ANN	=	Artificial Neural Network.
APE	=	Average Percent Relative Error (Er).
b	=	Bias.
BFG	=	BFGS Quasi-Newton
BHA	=	Bottom Hole Assembly
CGB	=	Conjugate Gradient with Powell/Beale Restarts
CGF	=	Fletcher-Powell Conjugate Gradient
CGP	=	Polak-Ribiére Conjugate Gradient
DOI	=	Depth Of Investigation
e	=	A Vector of Network Errors.
Ei	=	Error
FAL	=	Formation Analysis Log.
ϕ_n	=	Neutron Porosity.
g	=	gradient.
GDX	=	Variable Learning Rate Backpropagation
GOC	=	Geosteering Operation Center.
GR	=	Gamma Ray.
H	=	Hessian Matrix.
I	=	Identity Matirx.
J	=	Jacobian Matrix.
LM	=	Levenberg-Marquardt
logsig	=	Log-Sigmoid Transfer Function.
LWD	=	Logging While Drilling.
MaxErr	=	Maximum Absolute Percent Relative Error (Emax).
MinErr	=	Minimum Absolute Percent Relative Error (Emin).
n	=	number of Points.
NDCM	=	Neutron Density Correlation Method.
newcf	=	Cascade-Forward Backpropagation Network.
newelm	=	Elman Backpropagation Network.
newff	=	Feed-Forward Backpropagation Network.
OD	=	Outside Diameter.
OH	=	Open Hole.
OSS	=	One Step Secant
P	=	Pressure.
POH	=	Pull-Out of Hole.
purelin	=	Linear Transfer Function.
Q	=	The Number of Training Sets.

QC	=	Quality Control.
R	=	Correlation Coefficient.
ρ_b	=	Bulk Density.
Rd	=	Deep Resistivity.
RHOB	=	ρ bulk (Bulk density)
ρ_m	=	Measured Density.
Rm	=	Medium Resistivity.
RMSE	=	Root Mean Square Error.
ROP	=	Rate Of Penetration.
ρ_p	=	Predicted Density.
RP	=	Resilient Backpropagation
Rs	=	Shallow Resistivity.
SBD2	=	Smoothed Best Bin Bulk Density (g/cc).
SCAL	=	Smoothed Rapid Sample Caliper From density Tool (inch).
SCG	=	Scaled Conjugate Gradient
SCO2	=	Smoothed Best Bin Stand Off Correction (g/cc).
SEDP	=	Smoothed Phase Shift Derived Resistivity, Deep (ohm)
SEMP	=	Smoothed Phase Shift Derived Resistivity, Medium (ohm).
SESP	=	Smoothed Phase Shift Derived Resistivity, Shallow (ohm).
SFXE	=	Smoothed Formation Exposure Time (hrs).
SGRC	=	Smoothed Gamma Ray Combined (api).
SNP2	=	Smoothed Best Bin Pe Near (b/e).
SROP	=	Smoothed Rate of Penetration (ft/hr).
STD	=	Standard Deviation.
T	=	Temperature.
tansig	=	Tan-Sigmoid Transfer Function.
TD	=	Total Depth.
TFA	=	Tool Face Angle.
TNPL	=	Smoothed Thermal Neutron Porosity-Lst_Fixed Hole Size (v/v).
W	=	Weights.
Z	=	The Number of Weights and Biases in the Network.
μ	=	Iteration Parameter.

Subscripts

b	=	bulk.
n	=	neutron.

Superscripts

m	=	Measured.
p	=	Predicted.
T	=	Transpose.

خلاصة الرسالة

اسم الطالب: أحمد زكي العلي

عنوان الدراسة: تقدير مسامية الطبقات أثناء الحفر باستخدام الشبكة العصبية لتوجيه عملية الحفر.

التخصص :هندسة البترول
تأريخ الشهادة :يونيو 2009 م

الحفر الأفقي في طبقات زيت غير سميكة يتطلب قراءات ذات جودة عالية وفورية لتوجيه عملية الحفر في الإتجاه الصحيح. أغلب هذه القراءات تصل إلى السطح عبر وسائل قياس عن بعد مما يجعلها عرضة للضياع أو التغيير نتيجة لبعض تأثيرات البيئة والحفر. بعض المؤثرات على القراءات خلال الحفر هي : توسع بئر الحفر، عدم كفاءة آلة القراءة، اهتزاز آلة القراءه، انزلاق جهاز القراءه أثناء تغيير اتجاه الحفر. إن استخدام القراءات من دون أخذ هذه المؤثرات بعين الإعتبار قد يؤدي إلى اتخاذ قرارات فورية خاطئة، وإلى تحليل خاطئ لطبقات الحفر.

هنالك بعض ظروف الحفر التي تتطلب منا تقدير بعض القراءات نظرا لعدم توفرها بشكل جيد. هذه الظروف هي:

1- فقد جزء من قياسات القراءات نظرا لعطب عدسة القراءة للآلة.
2- ارسال جهاز الكثافة من دون الجهاز الموازن للآلة والذي يعد مهما في آلة قراءة الكثافة.
3- الحصول على قراءات غير منطقية لطبقات معلومة مسبقا مما يحذونا إلى عدم تصديقها.

هذه الرسالة تقدم وسائل لتصحيح القراءات في جهاز الكثافة أو تقديرها حال فقدها أثناء عملية الحفر باستخدام شبكة الأعصاب الإصطناعية لأجل الحصول على أفضل توجيه لعملية الحفر في المنطقة الصحيحة وإنتاج معلومات جيدة لتحليل قراءات الطبقات. يمكننا استخدام هذه التقنية في تقدير مسامية الطبقات لتكون متوافقة مع الآبار الأخرى. هذه الطريقة ذات قيمة عالية لخبراء الصخور في عملهم اليومي.

THESIS ABSTRACT

Full Name of Student: Ahmed Zaki Al-Ali

Title of Study: LWD POROSITY PREDICTION FOR WELL PLACEMENT USING NEURAL NETWORK

Major Field: Petroleum Engineering

Date of Degree: June 2009

Acquiring good quality logging while drilling (LWD) data is essential for geosteering wells drilled horizontally in narrow zones in oil bearing formation. The proper placement of those horizontal sections requires real time data from the formation as we drill through. Most of these data reach to the surface through different telemetry means which can be sometimes lost or distorted due to some environmental or drilling effects. Some of these effects on LWD data are: borehole wash-out, bad sensor detection, tool vibration, and sliding while changing azimuth or inclination angle. Utilizing raw LWD data without considering these factors may be misleading in making real time decisions as well as in the analysis of producing formation log (FAL).

LWD data needs to be predicted in some conditions such as when: 1. Part of the LWD measurements completely missed due to tool or sensor failure while drilling, 2. Running LWD density tool without stabilizer, which has a significant effect on the density tool reading, 3. Uncertainty in believing the tool response to a known formation.

This thesis provides means to correct LWD density data or predict missing LWD density data using artificial neural network (ANN) to optimize well placement correctly and produce good quality FAL. ANN method could be applied also to other porosity logs like neutron. Therefore, ANN technique can be used to predict porosity measurements to be consistent with other wells. This method provides significant value for petrophysicists in their daily operations.

CHAPTER 1

INTRODUCTION

Logging while drilling (LWD) generates two types of data. 1. Memory data, which is recorded in the memory of the tool, and 2. Real-time data, that comes to the surface as pulses in the drilling fluid. LWD is designed primarily for two purposes. Firstly, for well placement with real time measurements of porosity, lithology, and saturation. Secondly, for quantitative formation evaluation with the memory data.

One of the advantages of running LWD is that it measures formation properties shortly after the hole is cut. Therefore, borehole fluid invasion into formation that can affect log readings is also reduced. LWD can also be used for real time decisions to change the well path. In addition, no extra rig days are needed for logging after drilling.

Unfortunately, many drilling related factors can have effects on LWD data. Factors affecting LWD data quality include borehole wash-out, bad sensor detection, tool vibration, and sliding while changing azimuth or inclination angle. Utilizing raw LWD data without considering these factors may be misleading in making real time decisions as well as in producing formation analysis log (FAL). Therefore, a good understanding of raw LWD data and the factors affecting it is essential in petrophysics.

Part of the LWD measurements can be completely missed due to tool or sensor failure while drilling. It is common to pull out of hole to replace the failed tool with a back-up one. This practice can cost days of rig time. Depending on the type of tool that failed, data may be predicted with accuracy so rig time can be saved. Predicting missing data can be done using artificial neural network method (ANN) by utilizing data from different non-affected intervals in the same hole. Another example where you need to predict LWD data is when you run the LWD density tool without stabilizer, which has a significant effect on the density tool reading, or when one does not believe the tool response to a known formation. Therefore, it is recommended not to run the LWD density tool without stabilizer or to POH in case you doubt the tool response and instead predict the density data.

Artificial neural network (ANN) has been used successfully in many petroleum engineering practices. The use of ANN has concentrated mainly on predicting core properties (core porosity, core permeability, and core saturation) using conventional logs (Resistivity, Gama ray, Density, Neutron, and Sonic).

In this thesis, we will illustrate the methods of building the optimal artificial neural network model. This model is going to be used to correct for environmental and drilling artifacts in LWD density. It should be noted that ANN technique can be used to predict other porosity measurements like neutron log. Therefore, for any porosity tool, ANN technique can be used to predict porosity measurements to be consistent with other wells.

CHAPTER 2

PROBLEM DESCRIPTION

In this chapter we will illustrate with real examples some of the problems that are encountered while recording LWD data. Stating the objective of this study will be followed by literature review.

2.1 Environmental and Drilling Artifacts in LWD Data

Environmental and drilling artifacts in LWD data are often received due to factors such as borehole wash-out, bad sensor detection, tool vibration, and sliding while changing azimuth or inclination angle. Some of these factors that affect LWD data quality are discussed below.

2.1.1 Borehole Wash-Out: Effect of Borehole Size

Density Log. Density is a shallow measurement. Its depth of investigation (DOI) is about 0.5’ under normal conditions. Borehole rugosity affects its measurement. Small stand-offs can be corrected by using the spine-rib approach (Figure 2.1). Stand-offs larger than 1-inch may be difficult to correct, thus reported data will be inaccurate. Special techniques are needed to correct environmental artifacts in density data caused by large wash-out.

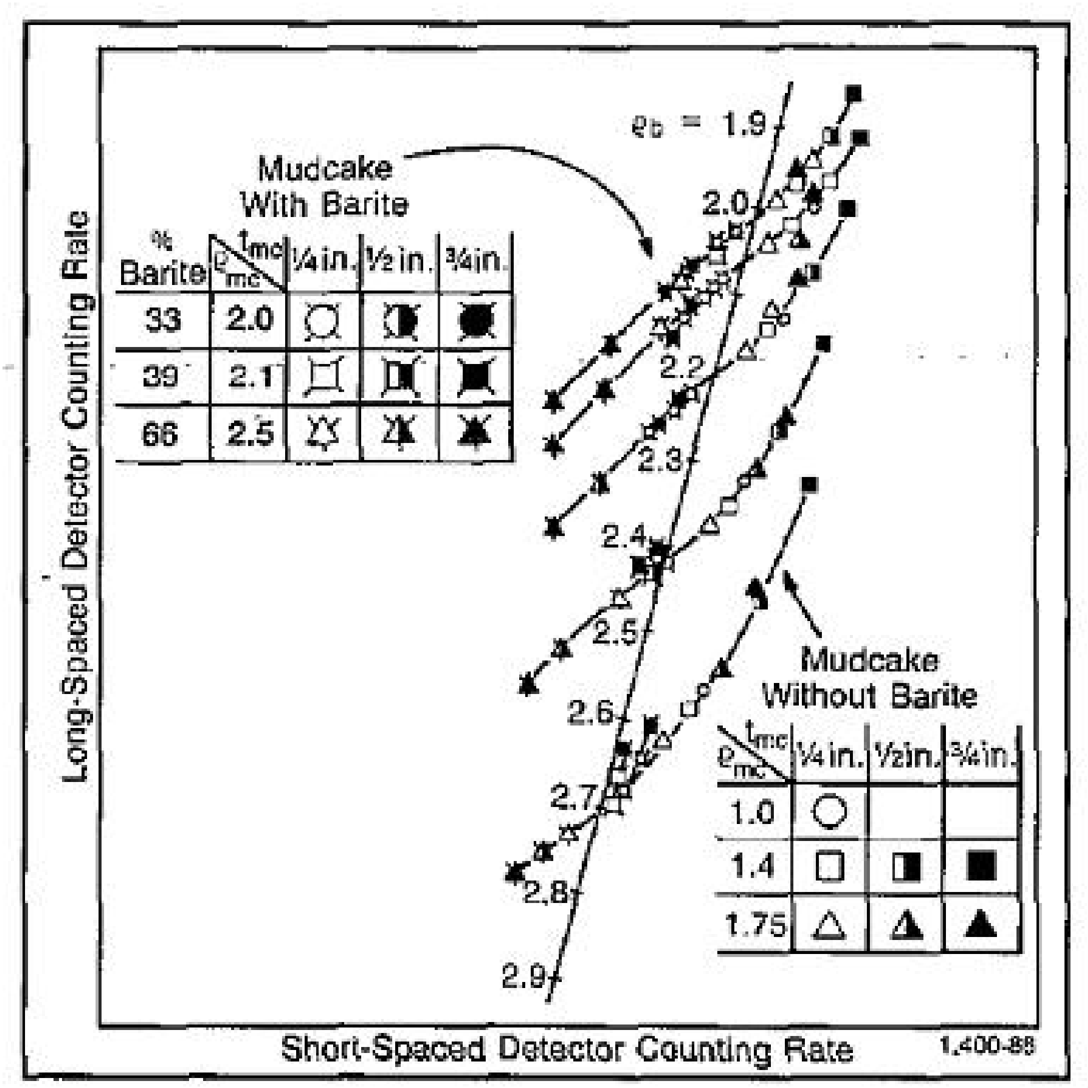


Figure 2.1: Spine-rib chart for density log correction for stand-off [20].

Neutron Log. Neutron log reads deeper than the density log; normally one foot. High porosity rocks slow down neutrons faster; reducing its DOI (figure 2.2). Since wash-out wellbore has 100% porosity, borehole size is the most important factor that affects the neutron data [20]. Thus, borehole size needs to be measured and its effects on neutron log need to be corrected. Without accurate borehole size measurement, methods are needed to correct the neutron data before it can be used.

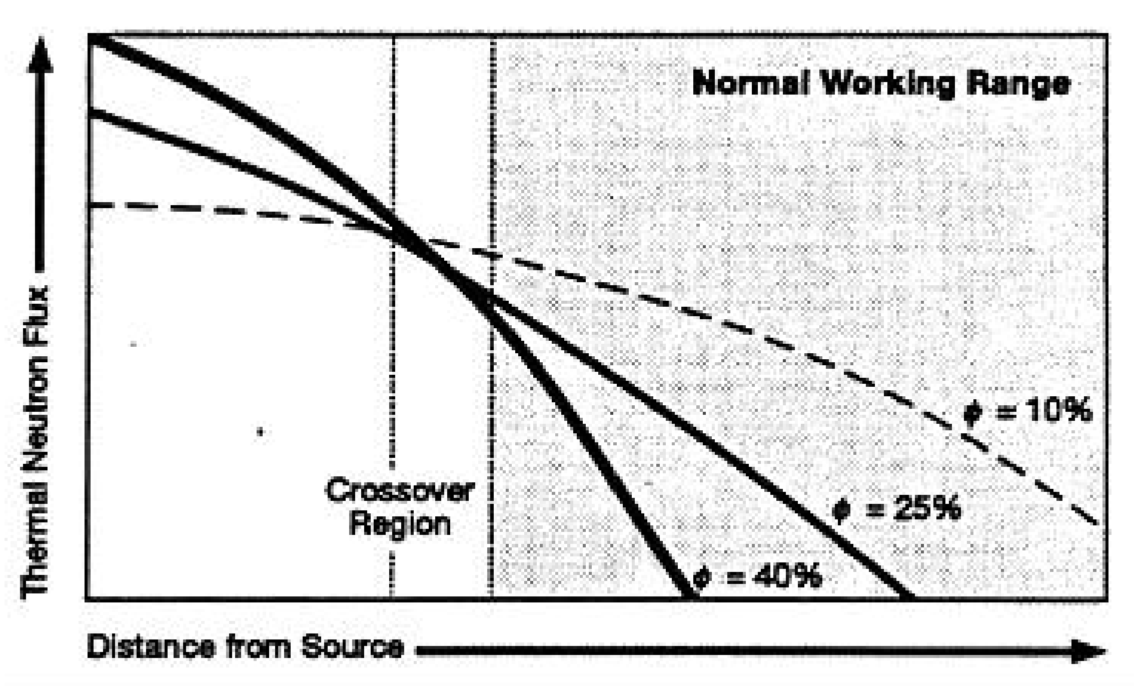


Figure 2.2: Neutron porosity depth of investigation [20].
Note that wash-out wellbore has 100% porosity.

Resistivity Log. Modern propagation resistivity logging tools have multiple depth of investigations (DOIs); ranging from a few inches to more than 100 inches. Borehole normally affects only the shallow measurements while the deeper measurements are less sensitive to borehole size (figure 2.3). For conventional formation evaluation or well placement, borehole wash-out effects on resistivity logs may be ignored; provided that wash-out is moderate.

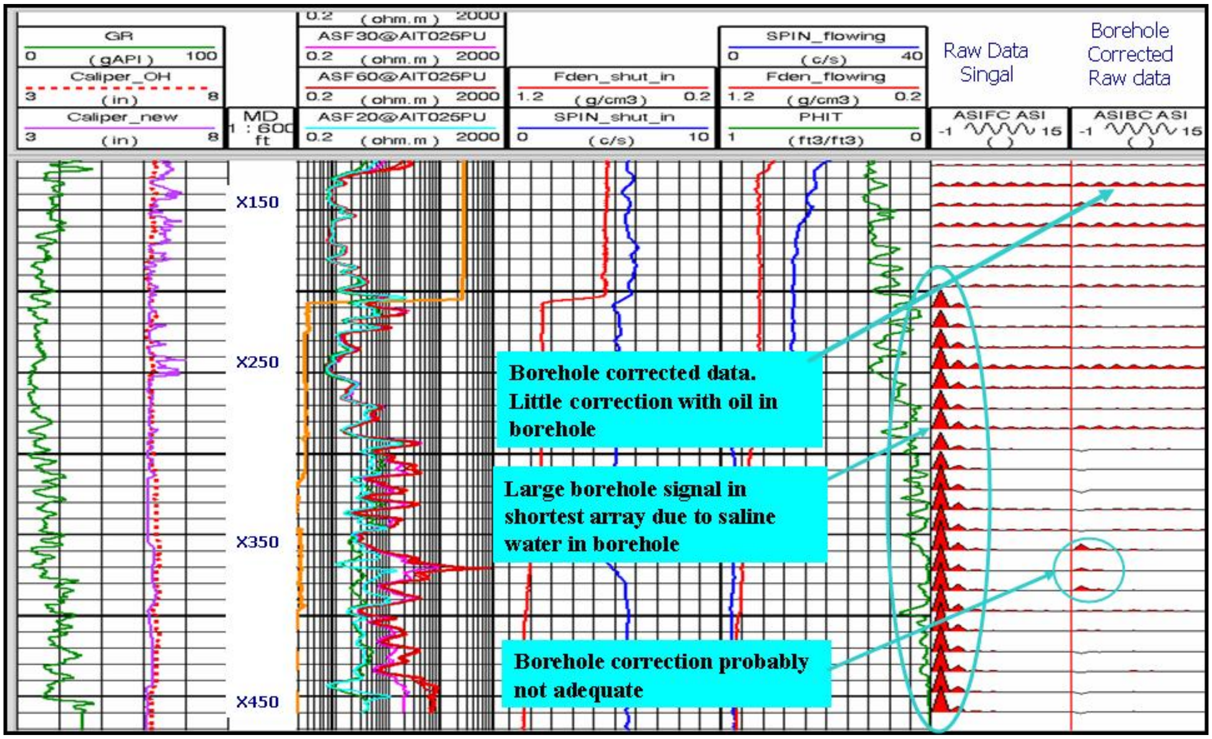


Figure 2.3: Borehole effects on resistivity [3].
Borehole has significant effects on shallow resistivity, but not on deep resistivity measurements.

2.1.2 Effect of BHA Sliding

A major difference between wireline logging and LWD is that LWD is part of the drilling bottom-hole assembly. Consequently, LWD rotates around the borehole while normal logging. In curve sections, sliding is required in order to build angle for horizontal drilling. Depending on the tool face angle (TFA) at the moment of sliding, LWD data quality, especially density data, may be affected by this sliding operation. Figure 2.4 summarizes potential effects of sliding on LWD density data quality. While sliding, if the LWD density sensor sits at the bottom of the hole (TFA=±180°) where the stand-off between the borehole and the measurement sensor is almost zero, then sliding has no effect on LWD density data quality (Figure 2.4A). On the other hand, if the sensor faces the top of the hole (TFA=0) where the stand-off is the largest, LWD density data will be affected the most (Figure 2.4B). Figure 2.4C illustrated a situation that is located between Figs. 2.4A and 2.4B.

If the borehole size is only slightly larger than the tool OD, the stand-off will be small irrespective TFA. In this case, sliding has little effect on LWD density data quality (Figure 2.4D).

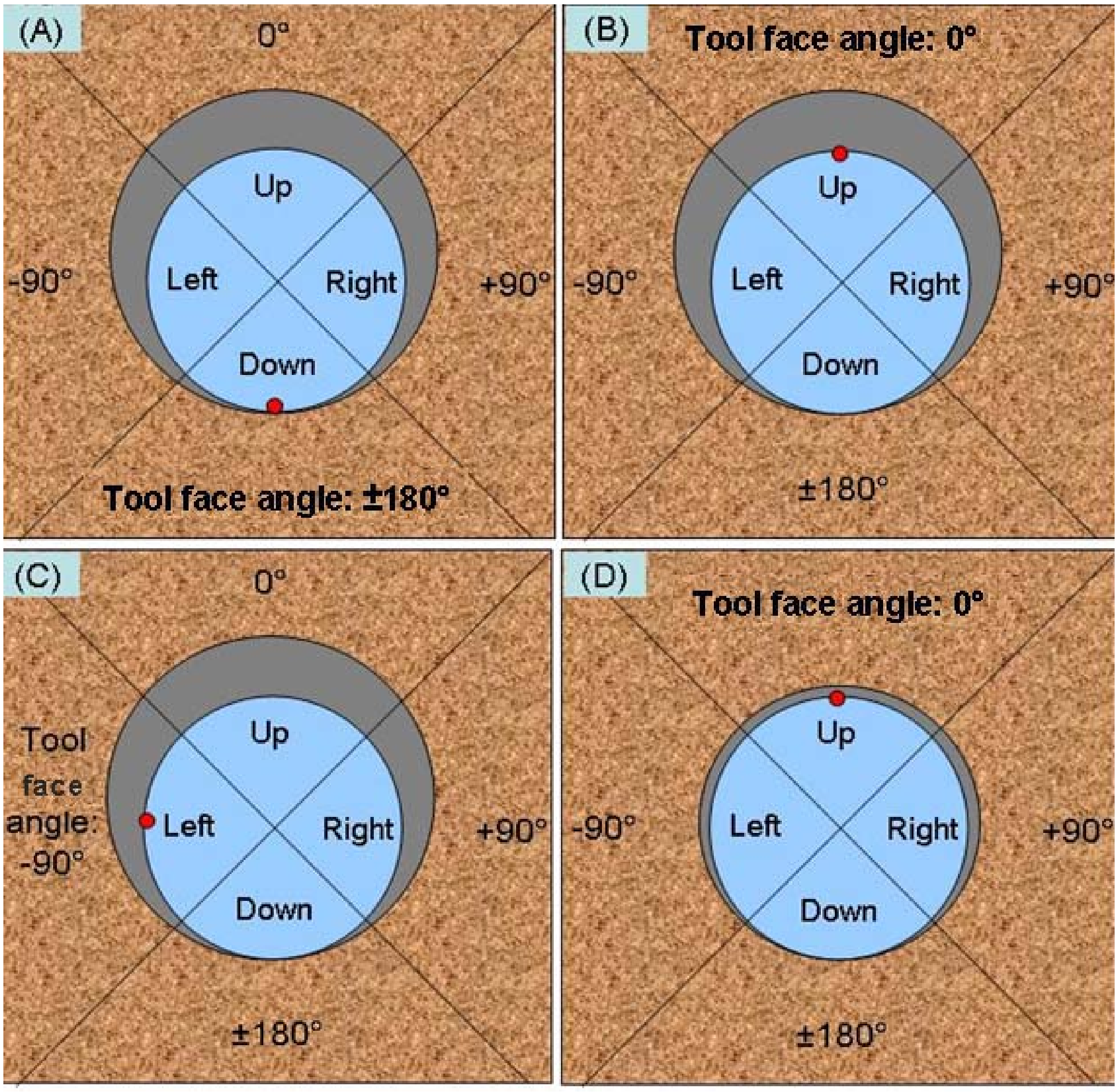


Figure 2.4: Effects of sliding on LWD density measurements.
This effect depends on tool face angle (TFA) and the difference between borehole size and tool OD. (A) No sliding effect if the sensor sits at the bottom of the hole (TFA~±180°). (B) Large sliding effect if the sensor faces to the top of the hole (TFA~0°) where the stand-off is the largest. (C) Sliding effect is reduced when the tool turns from TFA=0° to -90° due to decrease in stand-off. (D) Little sliding effect if the tool OD is only slightly less than the borehole size, irrespective of TFA.

2.2 LWD Data Quality Examples

Example 1: LWD in slim-hole – no sliding effect

As illustrated in Figure 2.4D, if the borehole size is only slightly larger than the LWD tool OD, then the tool sliding will have little effect on the LWD data quality. A field example of such situation is shown in Figure 2.5, where the 4-3/4” LWD density-neutron logging tool was used to log in a slim hole of 5 1/2”. No sliding effect was observed in this well.

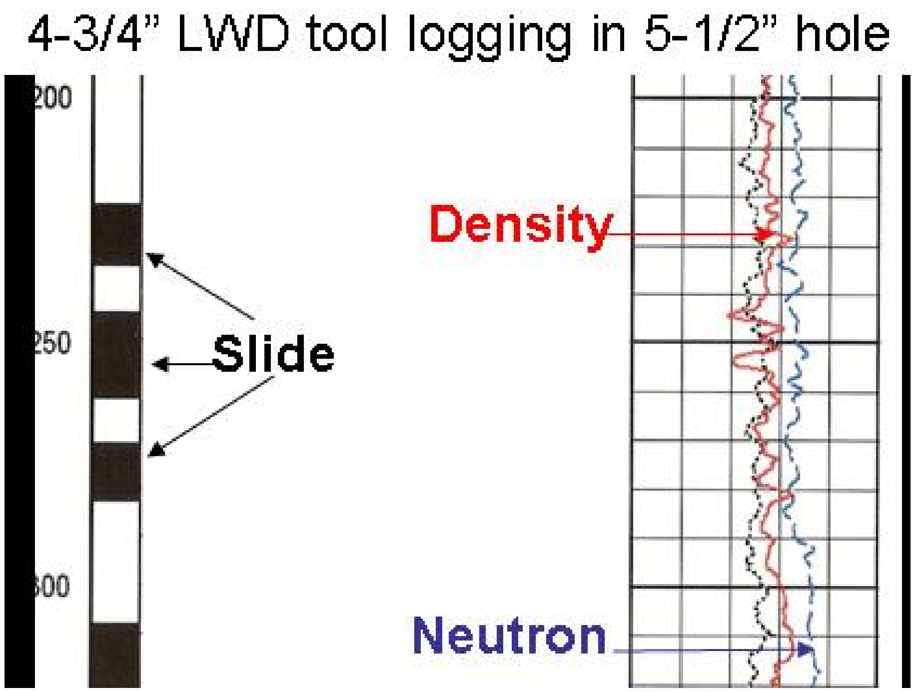


Figure 2.5: Effect of standoff correction while sliding.
Due to small stand-off between the borehole and the tool measurement sensor, sliding has little effect in LWD density data quality, as indicated in this figure.

Example 2: Borehole wash-out effect

If borehole is washed-out during drilling/circulating, the large washed-out borehole will have significant effect on LWD data quality, similar as the effect of large stand-off effect as illustrated in Figure 2.4B. A field example of borehole wash-out due to circulation during a trip out of the hole is shown in Figure 2.6. In this example, caliper indicated a large borehole which is corresponding to the abnormally low readings of the density sensor.

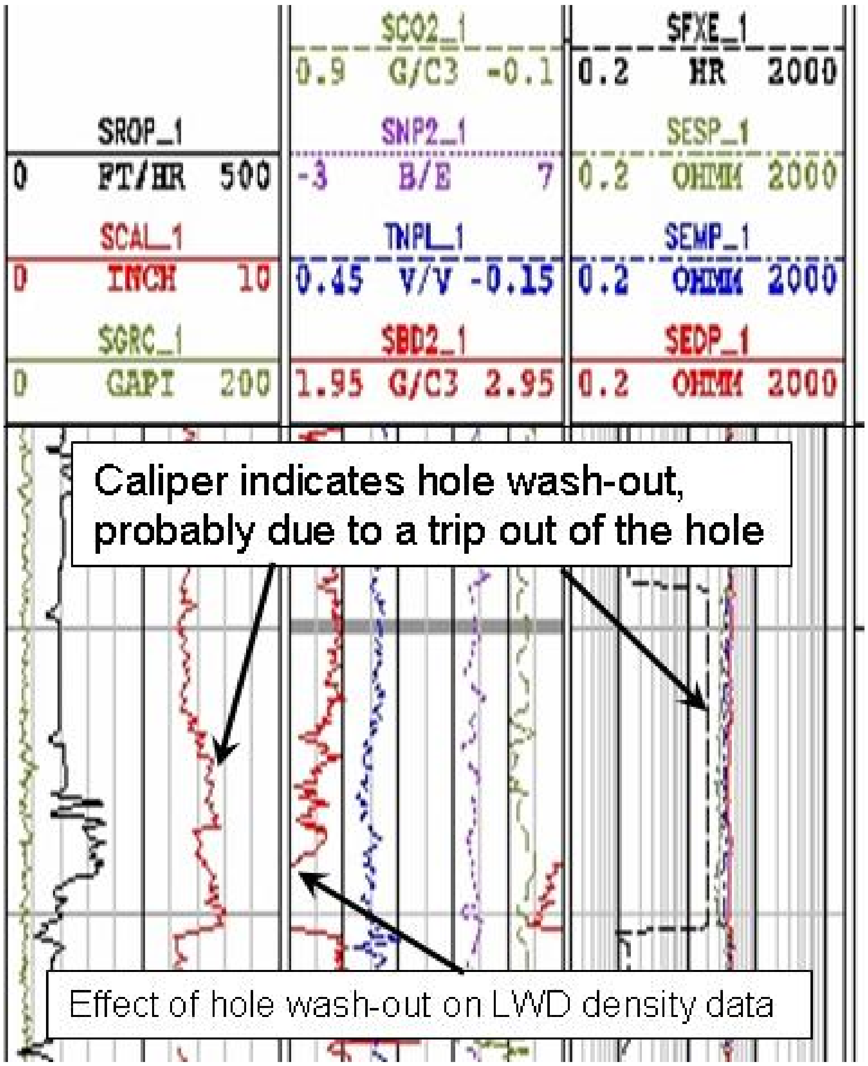


Figure 2.6: Effect of borehole wash-out on density data quality.

Example 3: LWD tool with sliding effect

If sliding is encountered during drilling while changing azimuth or inclination angle, the sliding will have significant effect on LWD data quality especially the density (figure 2.4). A field example of LWD with sliding effect is shown in Figure 2.7.

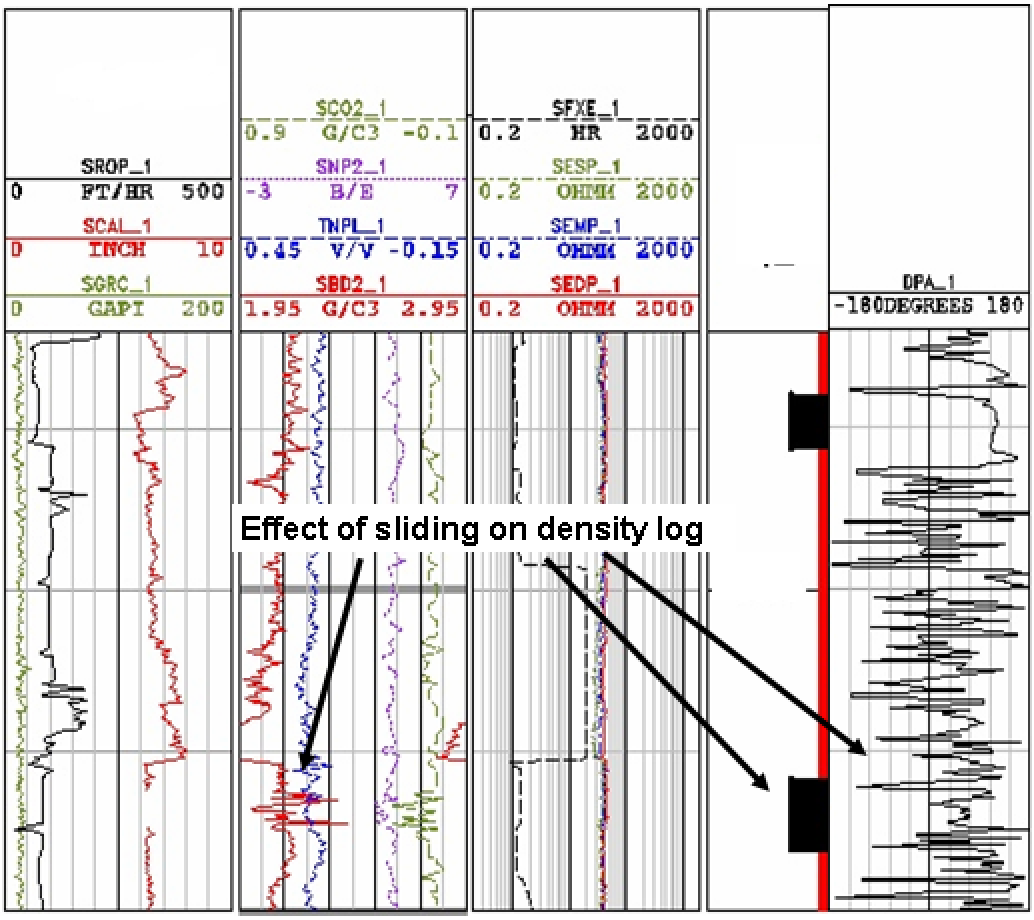


Figure 2.7: Effect of BHA sliding on LWD density log.

Example 4: LWD-Density tool failure

In some cases, one or more LWD tool sensors may fail during drilling. If the density tool sensor fails during drilling, for example, you have 2 options:

1- Pull the whole BHA out of hole and replace the LWD tool with a new one (a back-up LWD tool should always be available on location).

2- Continue drilling using neutron log for geosteering until a bit trip.

Geoseering Operation Centers (GOC) may decide to continue drilling to save rig time (porosity can be calculated using neutron log). For a petrophysicist, however, he will not be able to calculate lithology since it requires both logs (density and neutron). Moreover, the calculated porosity will not be consistent with other wells and hence will not be used for reserves calculations. Both porosity and lithology are essential elements in geological models and hence simulation models.

Example 5: Unable to run good quality LWD density log

The LWD density tool OD size is 4 ¾” without stabilizer. However, the LWD density tool requires stabilizer to obtain good measurements of the formation (it is not recommended to run the LWD density tool without stabilizer). Unfortunately, the LWD density tool size will increase to be 5 1/8” OD. Therefore, in slim-holes where the LWD density tool with stabilizer cannot be run while the rest of LWD tools can, the density data need to be predicted. Figure 2.8 shows the LWD density tool with stabilizer.

Predicting LWD density log is also beneficial in case of checking the response of LWD density tool. Instead of POH to check the LWD density tool on surface, we will be able to predict the density data down hole and compare it with the measured density values to determine whether the measured values are reliable for formation evaluation or not.

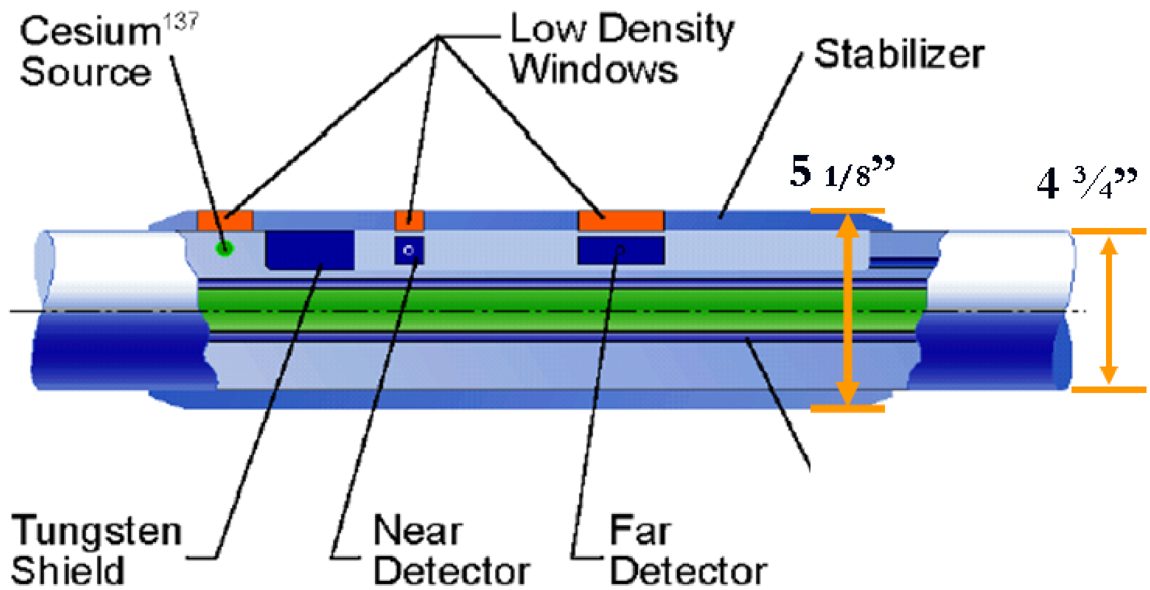


Figure 2.8: Stabilized litho density (SLD) [23].

2.3 Thesis Objectives:

The main objectives of this thesis are to first correct environmental and drilling artifacts in LWD density data and second to predict missing LWD density log in case of sensor failures and unavailability. Artificial Neural Network (more details on this technique will be explained in chapter 3) will be established to correct the artifacts in density data and results will be compared to results obtained using other methods (e.g. Averaging method and neutron density correlation method). For predicting missing LWD density log, neural network model will be constructed using LWD data obtained from the mother-bore of a multi-lateral horizontal well to train the model. LWD data will include (Gama Ray, Resistivity, Pressure, Temperature, Density, Neutron and Rate of Penetration). After that, the same neural network model will be used to predict density logs in another lateral in the same well and in a well that is far-away from this well (same formation).

2.4 Literature Review:

Artificial neural network (ANN) has been used successfully in many petroleum engineering practices. Most of the work that have been done (using ANN) is for predicting core properties (core porosity, core permeability, and core saturation) using conventional logs (Resistivity, Gama ray, Density, Neutron, and Sonic). No attempts have been found in the past to predict LWD density data from other conventional logs using ANN technique except for Olson [19] where he mentioned the use of neural network to improve and predict bulk density data. However, improved and predicted bulk density that he mentioned was for wire-line not for LWD.

2.5 Data Acquisition:

For repairing environmental and drilling artifacts in LWD density log, data were collected from 6 1/8" open hole (OH) well. The LWD density data that were collected was affected by hole wash-out and sliding.

For predicting missing LWD density data, we use a multi-lateral well. All laterals are OH. The main hole was used to study the case of LWD density sensor failure. In the case of inability to run LWD density log with stabilizer or checking the response of the LWD density log, we used the main hole for training the neural network model to predict the LWD density log in nearby lateral (nearby hole) and far-away well (far-away hole) as shown by figure 2.9.

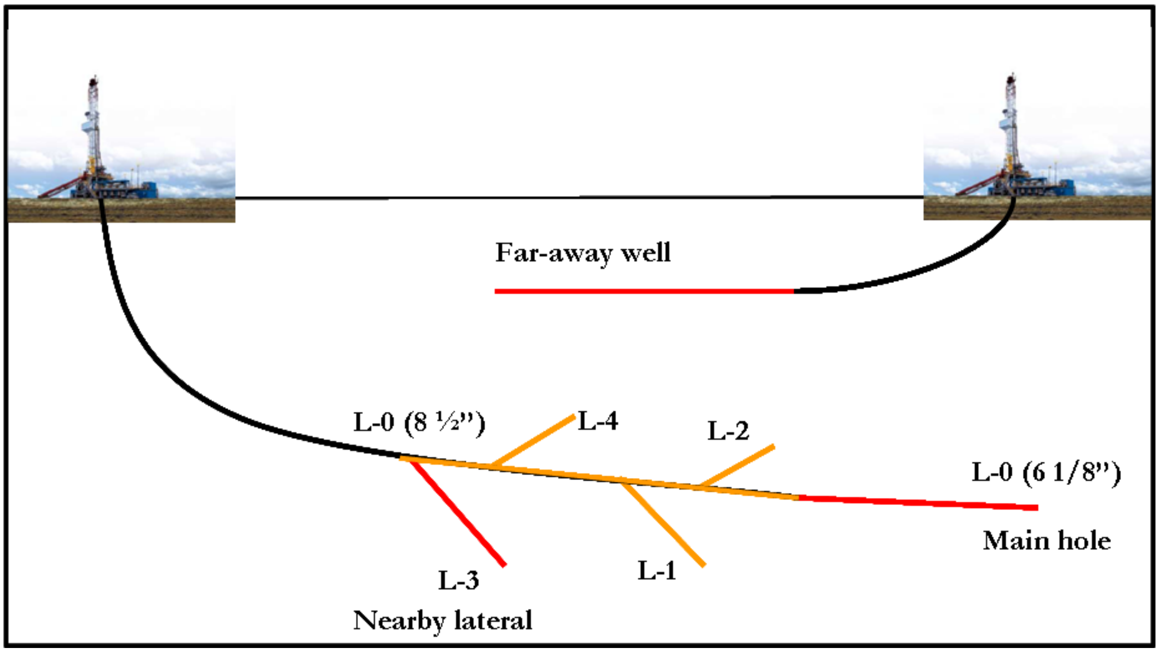


Figure 2.9: Case study for neural network model.
OH LWD data in the main hole was used to study the case of sensor failure. It was also used for training the neural network model to predict the LWD density log in nearby lateral (nearby hole) and in a far-away well (far-away hole) to study the case of inability to run LWD density tool with stabilizer or checking the response of the density log.

CHAPTER 3

ARTIFICIAL NEURAL NETWORK

3.1 Introduction:

Artificial neural network (ANN) or neural network is an information-processing (nonlinear mapping) system that has specific tasks which mimic the biological neural network. Our nervous system contains blocks which are nerve cells that are called neurons (Figure 3.1 shows two bipolar neurons). [18]

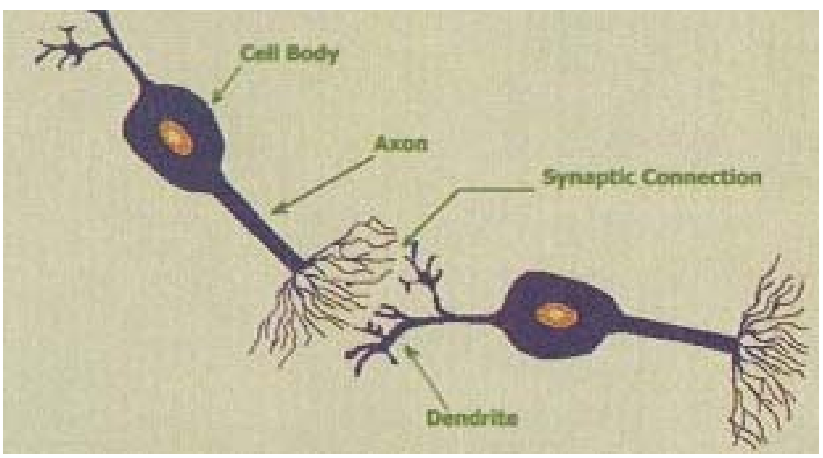


Figure 3.1: Two bipolar neurons [18].

A generalized mathematical model of the biological neural network was developed with the following assumptions [18]:

1. Information processing occurs in many simple elements that are called neurons (processing elements).
2. Signals are passed between neurons over connecting links.

3. Each connecting link has an associated weight, which multiplies the signal being transmitted.
4. Each neuron applies an activation function (usually nonlinear) to its net input to determine its output signal.

Figure 3.2 is a diagram that shows a typical neuron (processing element) in an artificial neural network. Every neuron has an output that is multiplied by the weight of the connection and enters the other neuron as input. Therefore, artificial neuron has many inputs and one output. Inside the neuron, inputs are applied to the activation function after they are summed and produce an output.[18]

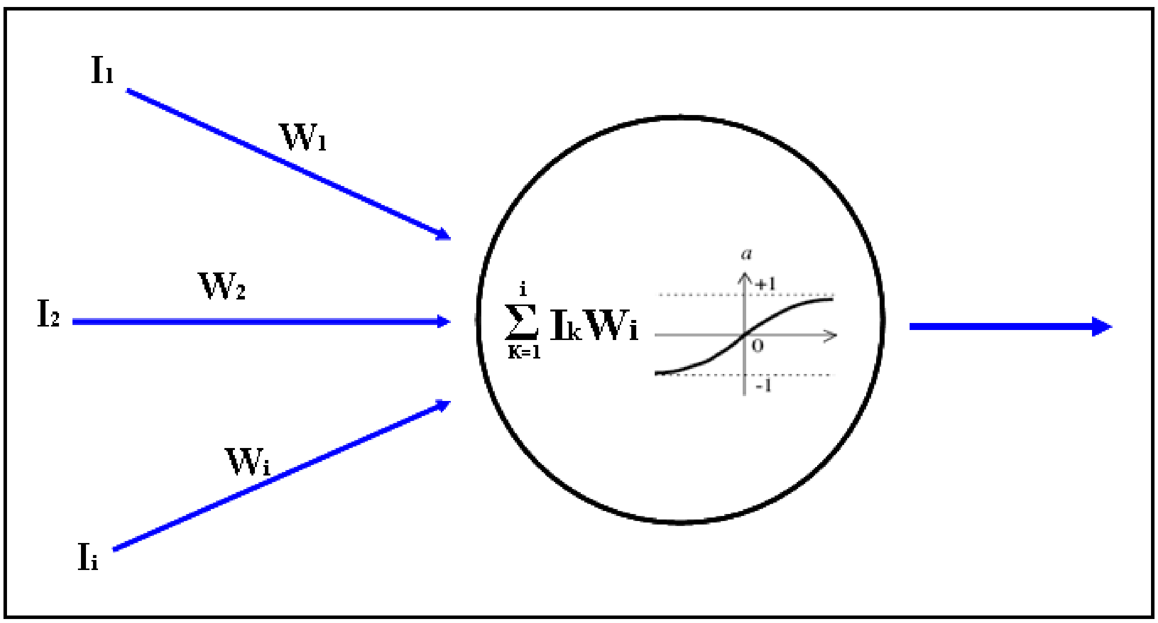


Figure 3.2: Artificial neuron (processing element).

3.2 Applications in the Oil and Gas Industry:

Artificial neural network has been used successfully in a variety of related petroleum engineering applications such as reservoir characterization, optimal design of stimulation treatments, and optimization of field operation. However, ANN should be used mainly to solve time-consuming or complex (nonlinear) problems that cannot be solved using conventional methods. [18]

3.3 Neural-Network Architecture and Operation:

Artificial neural network (ANN) is a collection of neurons that are grouped into layers. ANN model contain at least 3 layers: an input layer (corresponds to the number of input parameters that have a relationship with the target), one or more hidden layers (where the process occurs), and an output layer (the target that we need to predict using input parameters). The output layer is not limited to one neuron (one target), it can be built to generate more than one output. Figure 3.3 shows a schematic of a three-layer neural network model. [18]

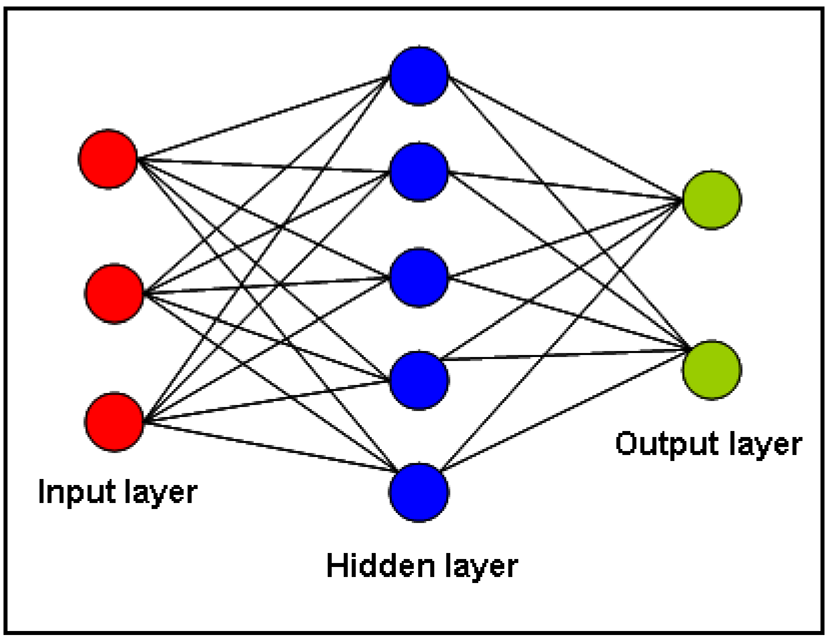


Figure 3.3: Three-layer neuron network.

In order to have a reliable model, ANN mode must passes through training phase and testing phase (a validation phase can be used after training; however, it is not a must). Training phase is completed by modification of the weights until it converges with the target set at the beginning (training stops when it completed the number of iteration that was set at the beginning or when it reaches the error required). The testing phase is basically testing the model that was generated in the training phase using actual values. The ANN model will predict the target and compare it with the actual values (measured values). [18]

ANN can be explained mathematically as a correlation that has dependent (input parameters) and independent (output, target) variables. The input and the weights on the inputs could be looked as vectors. For example, I_1, I_2 … I_n for inputs and W_1, W_2 ... W_n for weights. The product of the two vectors is the results (the dot or inner product). In a more simplified way, neural network model is a correlation that has matrix weights. The matrix size depends on the number of inputs (parameters) used in the training. [18]

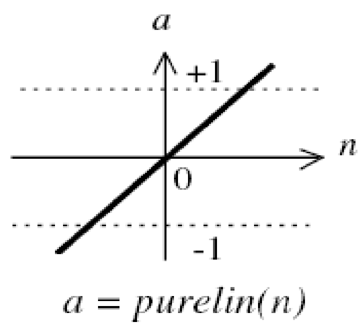
Training is accomplished by modification of the weights (depends on the type of training algorithm) until convergence is reached. The most commonly used training algorithm is the backpropagation algorithm. In this algorithm, network output is compared with the target output which is part of the training input data. The difference (error) is propagated backward through the network. During this process, the weights of the connections between neurons are adjusted (this process is continued in and iterative manner until convergence). [18]

3.4 Transfer Functions:

A transfer function is normally assigned to pass the signals after it is being processed inside the neuron to transfer the output of each neuron and layer from one to another. The most commonly used functions, out of many transfer function that are included in the neural network software, are shown below [10]:

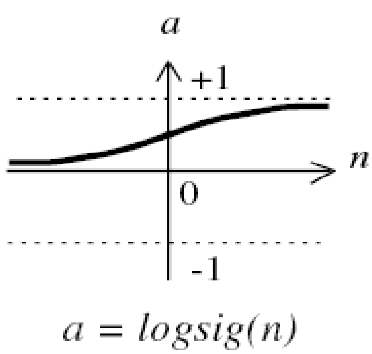
Transfer Function	Acronym
Linear Transfer Function	purelin(n)
Log-Sigmoid Transfer Function	logsig(n)
Tan-Sigmoid Transfer Function	tansig(n)

1- Linear Transfer Function [10]:



Neurons of this type are used as linear approximators.

2- Log-Sigmoid Transfer Function [10]:

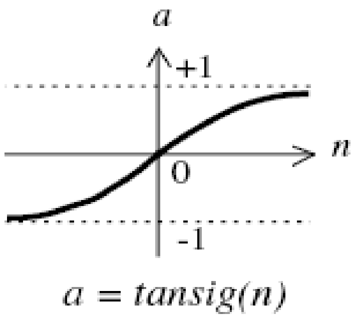


The sigmoid transfer function takes the input and squashes the output into the range 0 to 1. The input can have any value between plus and minus infinity.

This transfer function is commonly used in backpropagation networks because of its differentiability.

3- Tan-Sigmoid Transfer Function [10]:

Alternatively, the tan-sigmoid transfer function (tansig) can be used in a multilayer networks.

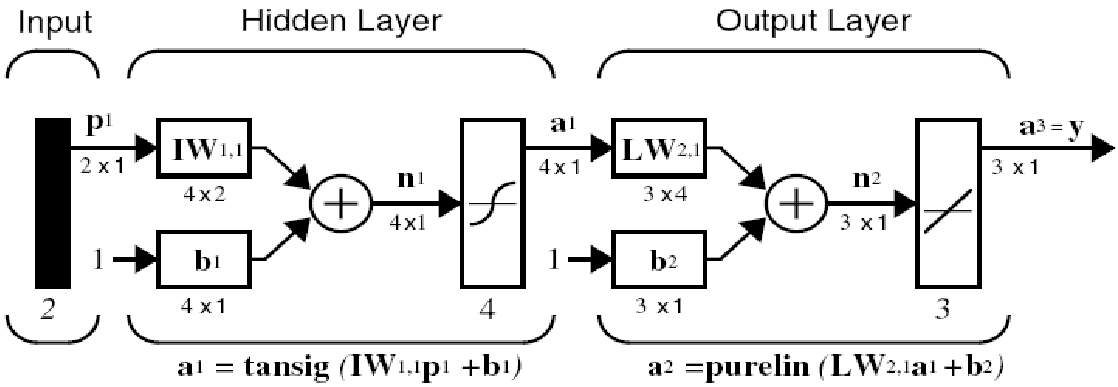


3.5 Feed-forward Network Function:

One or more hidden layers of sigmoid neurons followed by an output layer of linear neurons are often the constituent of a feedforward networks. To allow the network to learn nonlinear and linear relationships between input and output vectors a multiple layers of neurons with nonlinear transfer functions is used. The linear output layer lets the network produce values outside the range of –1 to +1.[10]

If you want to constrain the outputs of a network (e.g. between 0 and 1), on the other hand, then a sigmoid transfer function (such as logsig) should be used in the output layer. [10]

In multiple-layer networks, the number of layers determines the superscript on the weight matrices. The appropriate notation is used in the two-layer tansig/purelin network shown below. [10]



This network can be used as a general function approximator which can approximate any function with a finite number of discontinuities arbitrarily well, given sufficient neurons in the hidden layer. [10]

Creating a Network (newff)

In training a feed-forward network, the first step is to create the network object. A feed-forward network is created by the function newff. It requires three arguments and returns the network object. [10]

1. The first argument is a matrix of sample R-element input vectors.

2. The second argument is a matrix of sample S-element target vectors. The sample inputs and outputs are used to set up network input and output dimensions and parameters.

3. The third argument is an array containing the sizes of each hidden layer. (Targets determined the output layer size).

More optional arguments can be provided. For example, the fourth argument is a cell array. This array contains the names of the transfer functions to be used in each layer. The fifth argument contains the name of the training function to be used. In a three arguments feed-forward network, the default transfer function for hidden layers is tansig, the default for the output layer is purelin, and the default training function is trainlm (training functions will be explained later on in this chapter). [10]

Other Architectures for Backpropagation

Feed-forward networks with two-layer can potentially learn virtually any input-output relationship. As the number of layers increases, feed-forward networks might learn complex relationships more quickly. [10]

The function newcf creates cascade-forward networks, which are similar to feed-forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. For instance, a three-layer network has connections from layer 1 to layers 2, layer 2 to layer 3, and layer 1 to layer 3. In addition, the three-layer network has connections from the input to all three layers. These additional connections might improve the speed at which the network learns the desired relationship. [10]

Network Function	Acronym
Cascade-Forward Backpropagation Network	newcf
Elman Backpropagation Network	newelm
Feed-Forward Backpropagation Network	newff

3.6 Training ANN:

The network is ready for training once the network weights and biases are initialized. It can be trained for function approximation (nonlinear regression), pattern association, or pattern classification. The training process requires a set of examples of proper network behavior (network inputs and target outputs). The weights and biases of the network are iteratively adjusted during training to minimize the network performance function (e.g. MSE). [10]

For a given problem, it is very difficult to know which training algorithm will be the fastest. Choosing the fastest training algorithm depends on many factors such as the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition (discriminant analysis) or function approximation (regression). Table 3.1 lists the algorithms that are tested and the acronyms used to identify them in Matlab program. [10]

TABLE 3.1: List of training algorithms and their acronyms [10].

Acronym	Algorithm	Complete Name
LM	trainlm	Levenberg-Marquardt
BFG	trainbfg	BFGS Quasi-Newton
RP	trainrp	Resilient Backpropagation
SCG	trainscg	Scaled Conjugate Gradient
CGB	traincgb	Conjugate Gradient with Powell/Beale Restarts
CGF	traincgf	Fletcher-Powell Conjugate Gradient
CGP	traincgp	Polak-Ribiére Conjugate Gradient
OSS	trainoss	One Step Secant
GDX	traingdx	Variable Learning Rate Backpropagation

Levenberg-Marquardt (trainlm)

The Levenberg-Marquardt algorithm was designed to target second-order training speed without computing the Hessian matrix. When the performance function has the sum of squares form (which is typical in training feed-forward networks), then the Hessian matrix can be approximated as [10]:

$$\mathbf{H = J^TJ}$$

and the gradient can be computed as:

$$\mathbf{g} = \mathbf{J}^T\,\mathbf{e}$$

where **J** is the Jacobian matrix which contains first derivatives of the network errors with respect to the weights and biases, and **e** is a vector of network errors. The Jacobian matrix can be computed using a standard backpropagation technique that is much less complex than computing the Hessian matrix. [10]

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update [10]:

$$x_{k+1} = x_k - \left[J^T J + \mu \mathrm{I}\right]^{-1} J^T e$$

When the scalar **μ** is zero (it becomes Newton's method) using the approximate Hessian matrix. When **μ** is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum. Therefore, the aim is to shift toward Newton's method as quickly as possible. Thus, **μ** is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. For this reason, at each iteration of the algorithm, the performance function is always reduced. [10]

This algorithm appears to be the fastest method for training moderate-sized feed-forward neural networks (up to several hundred weights). In addition, it has an efficient implementation in MATLAB software, since the solution of the matrix equation is a built-in function. Therefore, its attributes become even more pronounced in a MATLAB environment. [10]

Reduced Memory Levenberg-Marquardt (trainlm)

The main disadvantage of the Levenberg-Marquardt algorithm is that it requires the storage of some matrices which can be quite large for certain problems. The size of the Jacobian matrix is **Q x Z**, where **Q** is the number of training sets and **Z** is the number of weights and biases in the network. It turns out that this matrix does not have to be computed and stored as a whole. If you were to divide the Jacobian into two equal sub-matrices, for instance, you could compute the approximate Hessian matrix as follows [10]:

$$H = J^T J = \left[J_1^T \; J_2^T \right] \times \left[\begin{matrix} J_1 \\ J_2 \end{matrix} \right] = J_1^T J_1 + J_2^T J_2$$

Therefore, the full Jacobian does not have to exist at one time. The approximated Hessian can be computed by summing a series of sub-terms. Once one sub-term has been computed, the corresponding sub-matrix of the Jacobian can be cleared. [10]

3.7 Benefits of Neural Networks:

The computing power of ANN was driven by its extraordinarily parallel distributed structure and its ability to generalize through learning (generalization is predicting outputs with high accuracy for inputs that are not encountered during training). These two capabilities allowed the neural networks to solve complex problems. [13]

Some of the most useful properties and capabilities for using neural networks are as follows:

1. ***Nonlinearity***: the neuron of ANN model can be linear or nonlinear. The nonlinearity is distributed throughout the network. This is very important in solving nonlinear problems. [13]

2. ***Input-Output Mapping***: supervised learning (learning with teacher), which is a popular paradigm, involves neural network weights adjustment by applying a set of known training samples (or task examples). Each example consists of defined input signal and a corresponding desire response. First, the network is presented with example that is randomly picked from the set. Second, the weights of the network are adjusted to minimize the difference between the preferred response and the actual one. The actual response is produced by the input signal in accordance with an appropriate statistical criterion. This training of network is repeated through many examples in the set until the network reaches a steady state (no significant changes in the weights for every new example in the set). [13]

3. ***Adaptivity***: the weights in the neural networks have the capability to change (adapt) in the surrounding environment. If the neural network trained to operate in a certain environment, it can be retrained easily to operate in a new condition that has minor changes to the original environmental condition. [13]

3.8 Challenges in Neural Networks:

ANN has some challenges that need to be studied before building neural network model. Although ANN is widely used in the petroleum industry and has many successful results, these challenges were not solved properly. A thorough study involving trial and error technique in addition to independent verification is the best method to overcome these challenges. The most important challenges that neural network has are discussed below:

1. ***Memorization (overtraining)***: Training with an iterative process (e.g. backpropagation networks) can cause the network to memorize the set of data. Once it memorizes it, it will not be capable of generalization despite that it fits well with the training data stet. To overcome this problem, it is recommended to have only one hidden layer and less number of neurons. It is also recommended to test the neural network model using separate data set by predicting the target values and compare them with the measured values to study the effect of memorization. In case of memorization, the network model will not predict the target values properly and you will have high error.

2. ***Determining the number of hidden layer***: As mentioned earlier, it is recommended to use less hidden layers. If the model generated using only one hidden layer can predict the target with good confidence, then there is no need to increase the number of hidden layer. The number of hidden layer will affect also the speed of processing. As the number of hidden layer decreases, the neural network model will predict the target faster.

3. ***Determining the number of neurons in the hidden layer***: This challenge was discussed many times in neural network modeling and doesn’t have precise answer since it is case sensitive. The best way to find the optimal number of neurons is through trial and error.

4. ***Determining the type of network function***: Similar to determining number of neurons in the hidden layer, this challenge doesn’t have precise answer. Although backpropagation networks seems to be the best network in petroleum engineering practices, it has different types that need to be tested through trial and error to find the optimal one.

Finding the optimal number of neurons in the hidden layer and the type of network function is case sensitive. It is recommended to study them for every neural network model.

3.9 Building ANN Model:

Before building any neural network model, understating of the problem that needs to be solved and the objective of building the model is required. In this study, we would like to predict the density log in case of sensor failure or correct environmental and drilling artifacts in data detections. Therefore, we will have only one output which is LWD density log.

The number of input data depends on how much data you have and how much they are correlated with the density log (the target). Logging wile drilling (LWD) usually has Gamma Ray (GR), Rate of Penetration (ROP), Neutron, Density, Resistivity (deep-Rd, medium-Rm, and shallow-Rs), Pressure (P), and Temperature (T). Table 3.2 below shows correlation matrix results of LWD data. A detail of correlation matrix is shown in the Appendix.

TABLE 3.2: Correlation matrix results with respect to LWD data.

	Density	P	T	GR	Rd	Rm	Rs	ROP	Neutron
Density	1	-0.42	-0.42	-0.38	0.31	0.50	0.42	-0.33	-0.49
P	-0.42	1	1	0.26	-0.30	-0.24	-0.11	-0.02	-0.16
T	-0.42	1.00	1	0.26	-0.30	-0.24	-0.11	-0.02	-0.16
GR	-0.38	0.26	0.26	1	-0.21	-0.32	-0.16	0.25	0.21
Rd	0.31	-0.30	-0.30	-0.21	1	0.48	0.40	-0.20	-0.20
Rm	0.50	-0.24	-0.24	-0.32	0.48	1	0.88	-0.35	-0.55
Rs	0.42	-0.11	-0.11	-0.16	0.40	0.88	1	-0.31	-0.55
ROP	-0.33	-0.02	-0.02	0.25	-0.20	-0.35	-0.31	1	0.56
Neutron	-0.49	-0.16	-0.16	0.21	-0.20	-0.55	-0.55	0.56	1

Most of log data show good correlation with the density log. However, we need now to study the physics of each tool before we use it for training. Although pressure and temperature have good correlation with the density log, they are not good logs for training. Because the well is horizontal, pressure and temperature will not change much (pressure and temperature are strong function of depth) and hence will not indicate the changes in the density log. ROP has a strong correlation with the density log since both are function of porosity. However, ROP is also a strong function of weight on bit and tooth wear. Therefore, it is recommended not to use it in the presence of other porosity tools (e.g. neutron or sonic).

Resistivity measurements show good correlation with LWD density log. As the resistivity reading of the formation increases, the porosity reading of the formation decreases hence the LWD density log increases. Therefore, resistivity tools are good data for training the LWD density log. However, there are three tools that read the resistivity of the formation. They are (deep-Rd, medium-Rm, and shallow-Rs). It is recommended to choose Rd because it reads the true resistivity of the formation. Rm and Rs, on the other hand, have less DOI and since they have strong correlation (table 3.2) one of them is enough to be used for training the LWD density log. Because the LWD density log is a shallow measurement (DOI = 6"), we decided to select Rs for training (effect of invasion on resistivity tool is minimal in LWD reading compared to wire-line).

Studying these logs conclude that GR, Neutron, Rd, and Rs (ROP is optional depends on the situation) are the best tools for training the model. Therefore, we will have 4 inputs to train our target which is the density log.

3.10 Neural Network Model Optimization:

As mentioned earlier, determining the number of hidden layers, number of neurons in the hidden layer, type of transfer function, type of network function, and type of training algorithms are legitimate questions with no precise answers because they are case sensitive. Therefore, we need to study every one of them for building the optimal neural network model for our problem.

3.10.1 Determining the number of hidden layer

In general, fewer numbers of neurons with less hidden layers is better to reduce the effect of memorization. This is proved by figures 3.4 to 3.6 which show the effect of changing the number of hidden layers on correlation coefficient (R), average absolute percent relative error (AAPE), and root mean square error (RMSE) [refer to Appendix A]. Notice that as the number of hidden layers increases, effect of memorization increases (figures 3.5 and 3.6). Although the neural network model predicted the training data with high accuracy, it wasn't capable of predicting a separate set of data in the nearby hole.

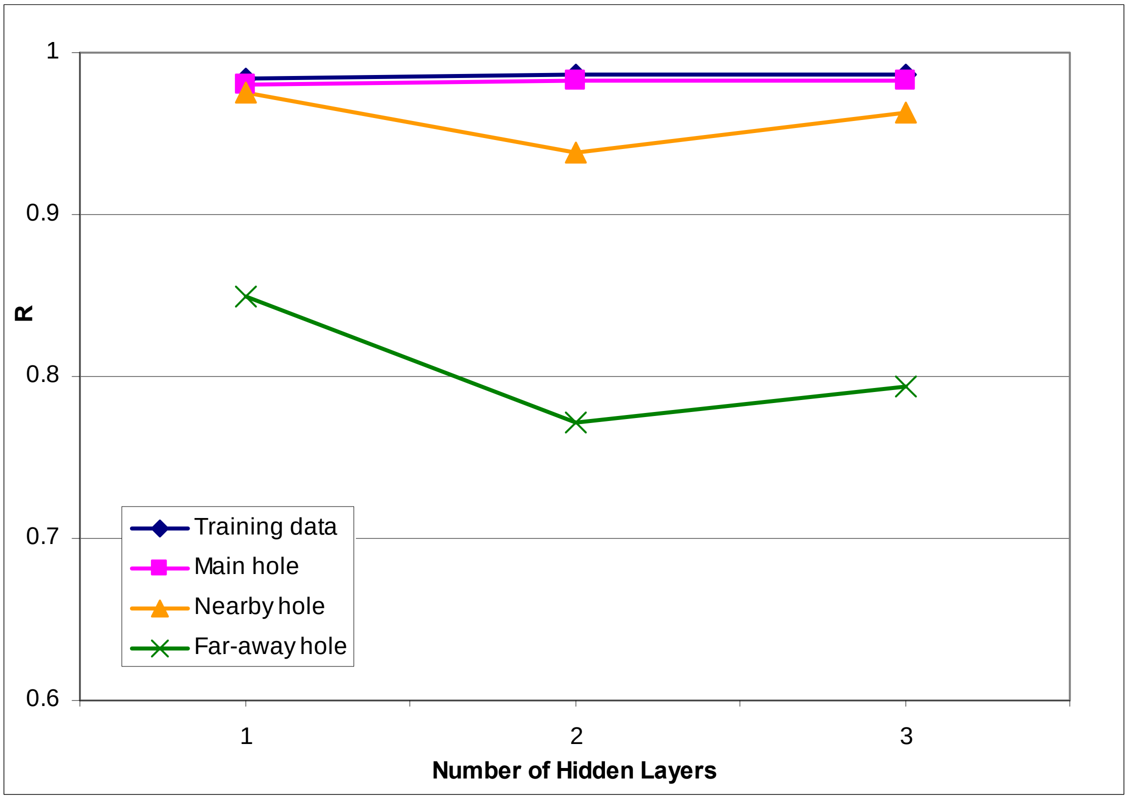


Figure 3.4: Effect of hidden layers on correlation coefficient.

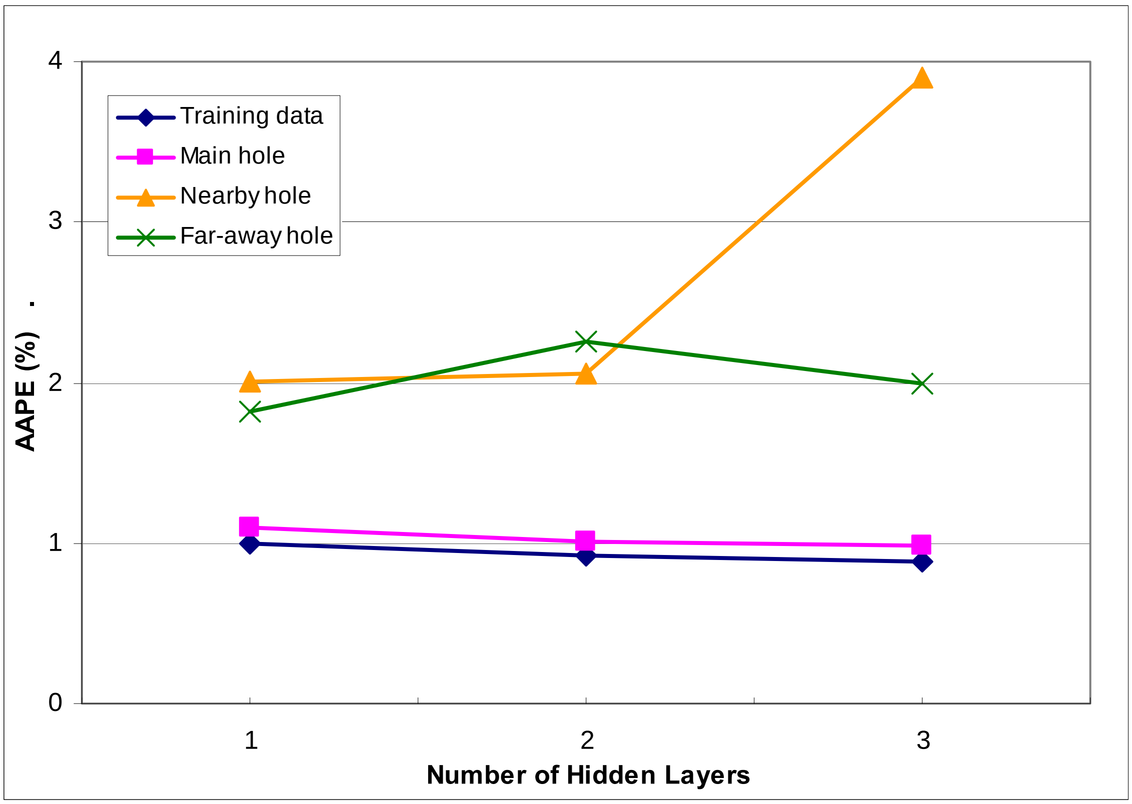


Figure 3.5: Effect of hidden layers on average absolute percent relative error.

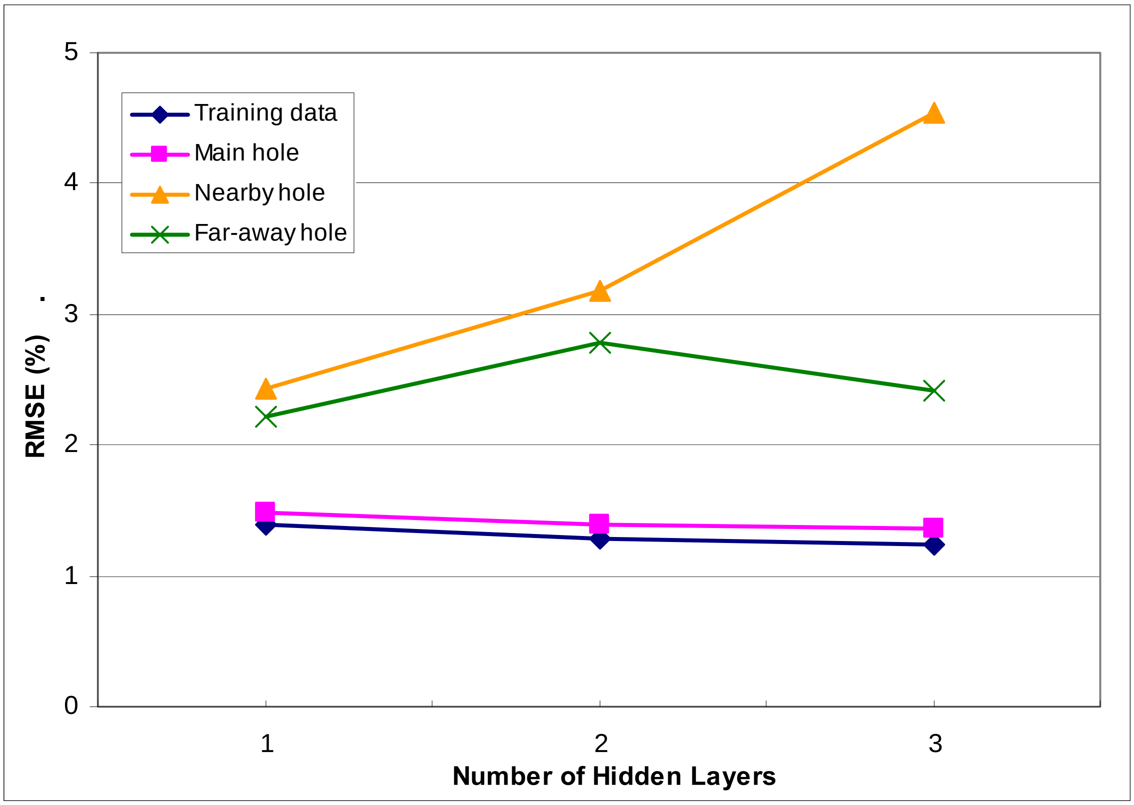


Figure 3.6: Effect of hidden layers on root mean square error.

3.10.2 Determining the number of neurons in the hidden layer

Determining the optimal number of neurons in the hidden layer requires trial and error technique. Figures 3.7 to 3.9 show the effect of changing number of neurons in the hidden layer on R, AAPE, and RMSE. These figures show that the optimal number of neurons in the hidden layer is ten since it has high correlation coefficient values as shown by figure 3.7 and lower error values as shown by figure 3.8 and figure 3.9.

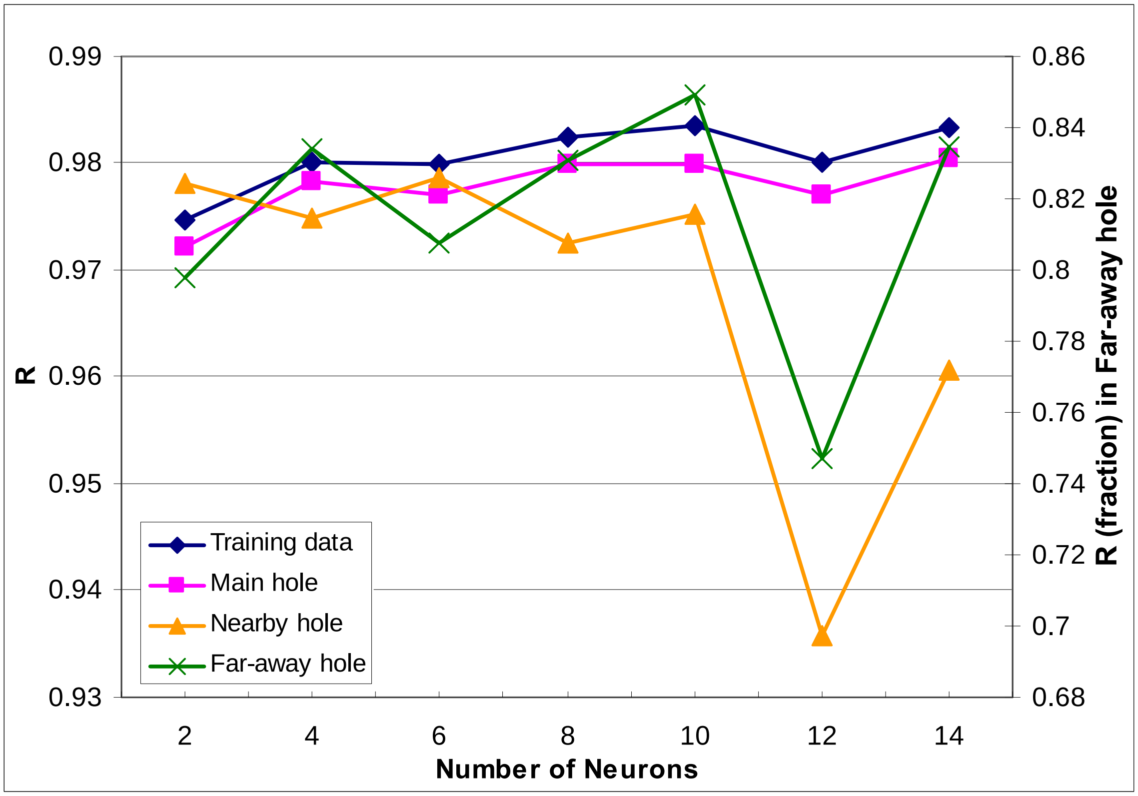


Figure 3.7: Effect of number of neurons on correlation coefficient.

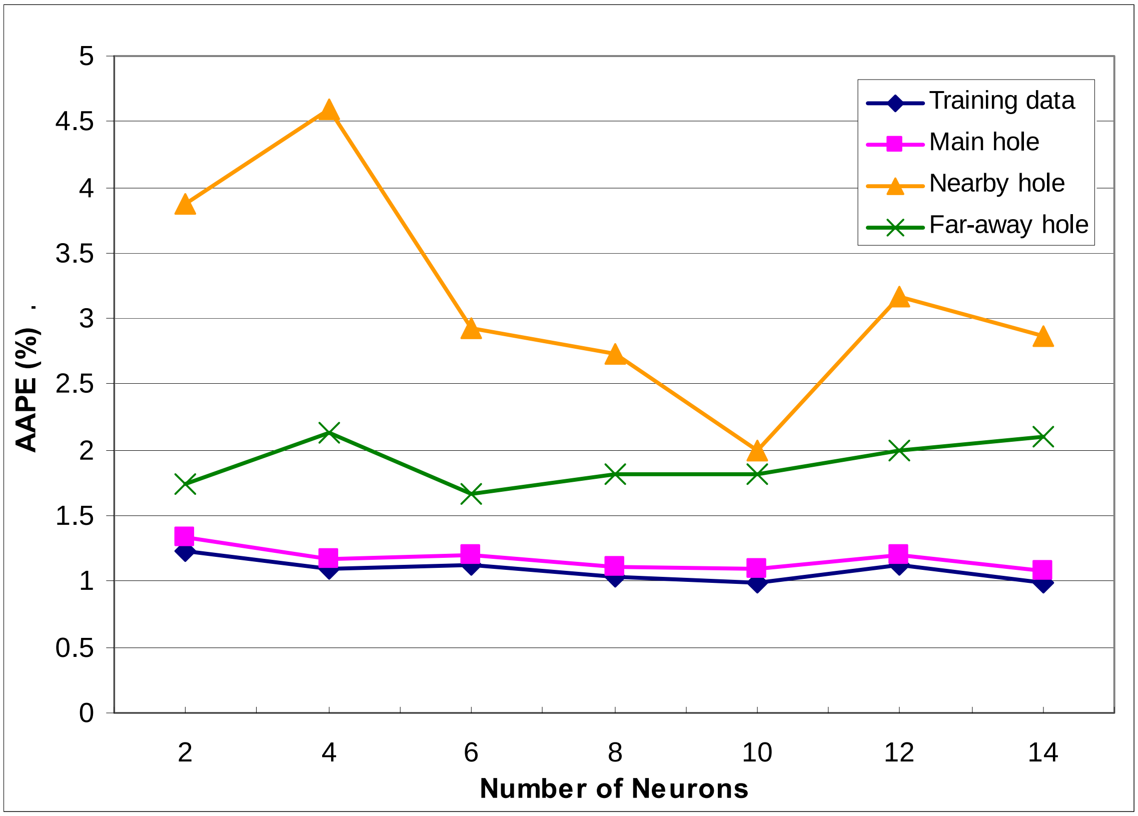


Figure 3.8: Effect of number of neurons on average absolute percent relative error.

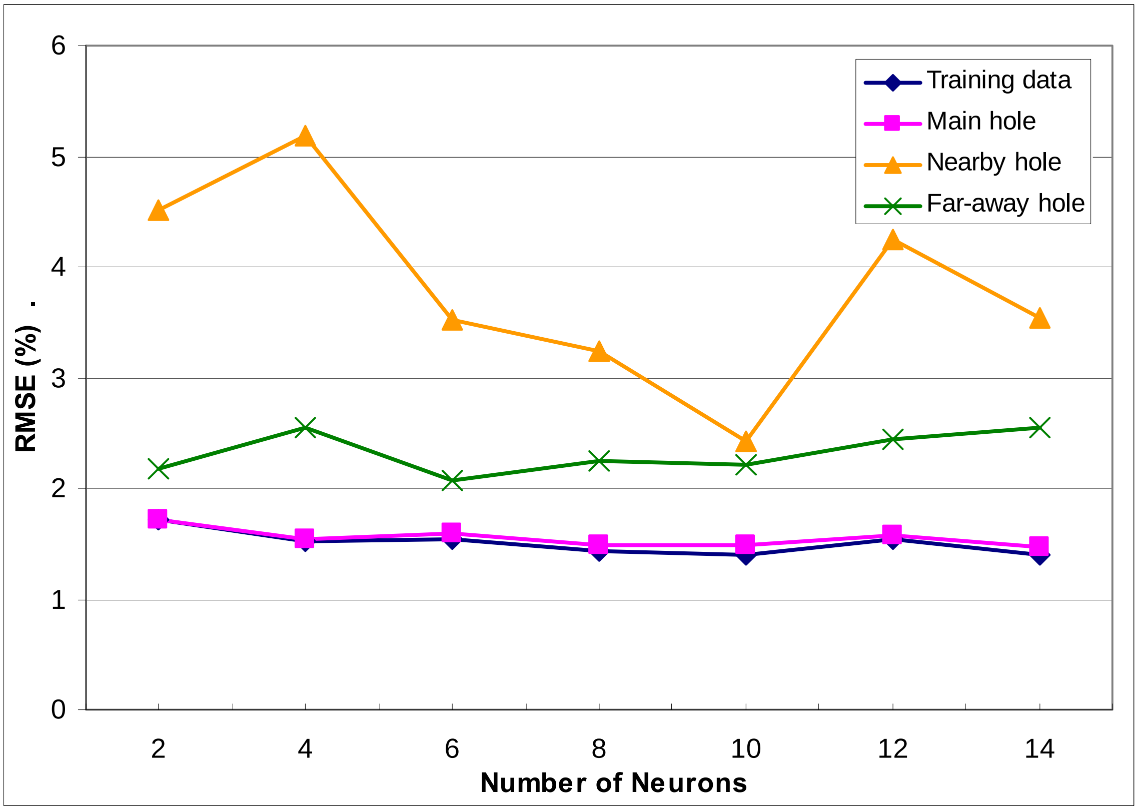


Figure 3.9: Effect of number of neurons on root mean square error.

3.10.3 Determining the type of transfer function

Determining the type of transfer function is similar to determining the number of neurons in the sense that it requires trial and error analysis. Figures 3.10 to 3.12 show the effect of changing number of neurons in the hidden layer on R, AAPE, and RMSE. The optimal type of transfer function is **tansig** since it has high correlation coefficient values as shown by figure 3.10 and lower error values as shown by figures 3.11 and 3.12.

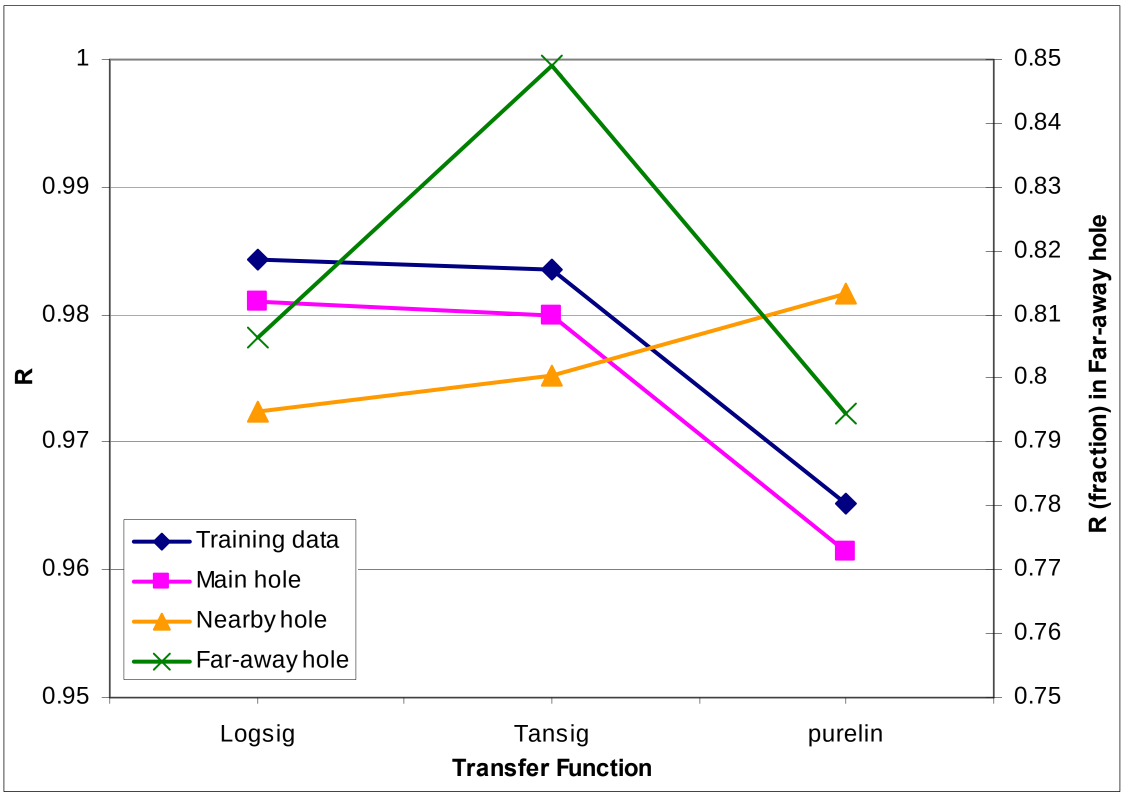


Figure 3.10: Effect of transfer function on correlation coefficient.

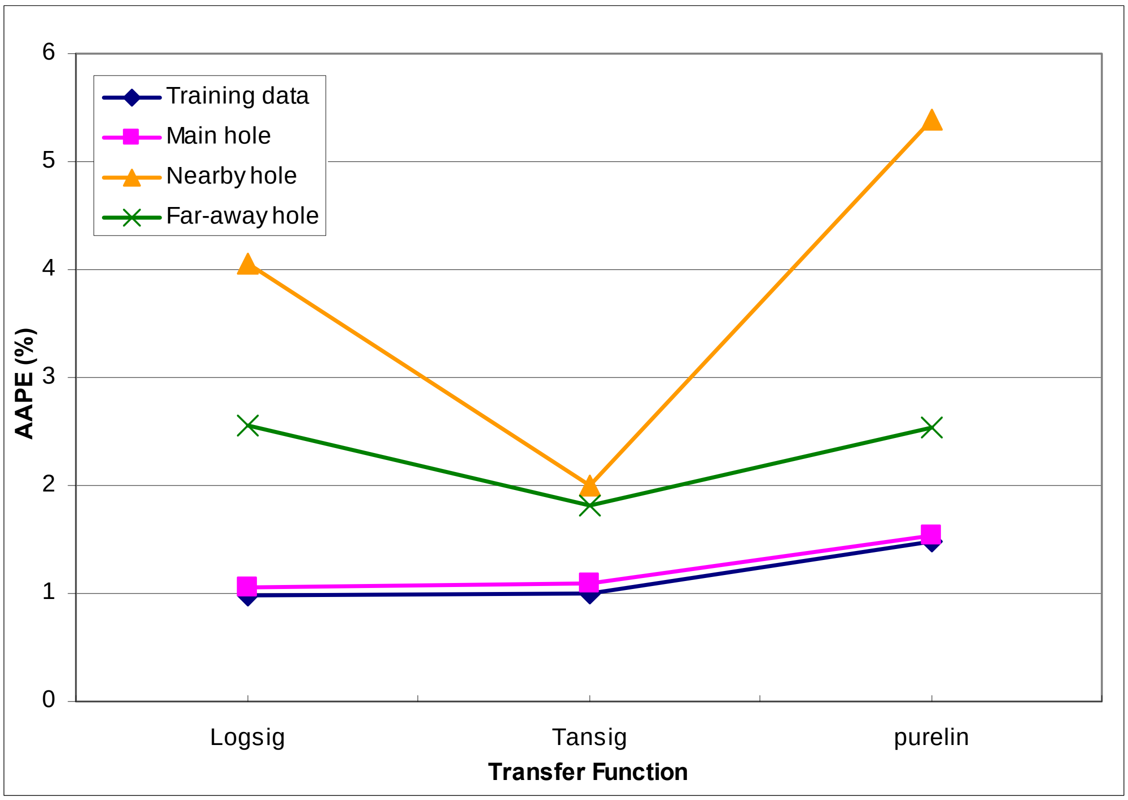


Figure 3.11: Effect of transfer function on average absolute percent relative error.

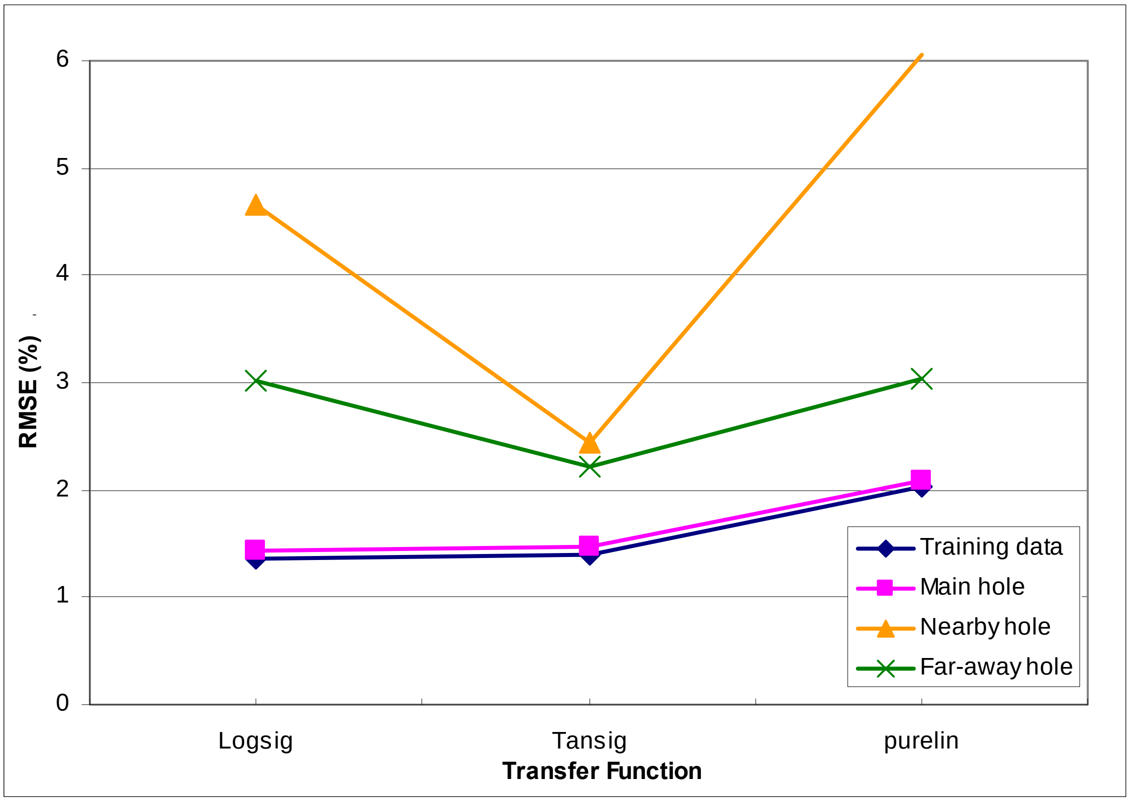


Figure 3.12: Effect of transfer function on root mean square error.

3.10.4 Determining the type of network function

Similarly, the optimal type of network function is **newff** since it has high correlation coefficient values as shown by figure 3.13 and lower error values as shown by figures 3.14 and 3.15.

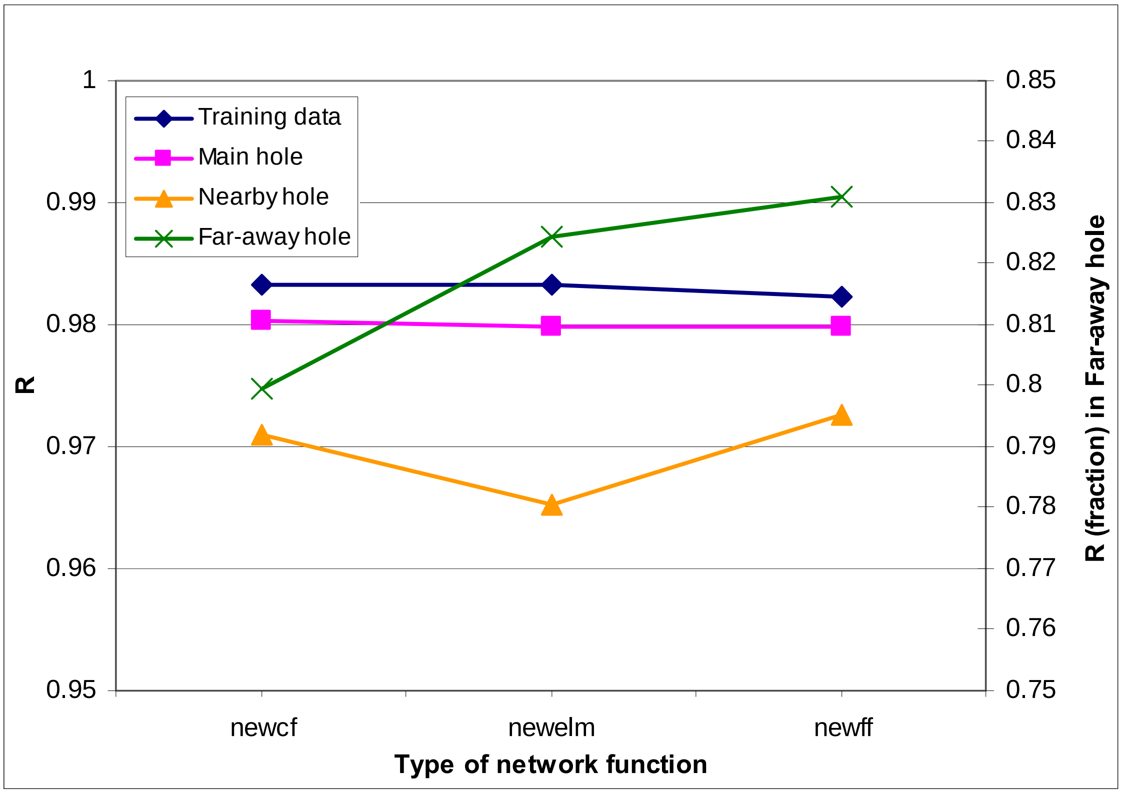


Figure 3.13: Effect of network function on correlation coefficient.

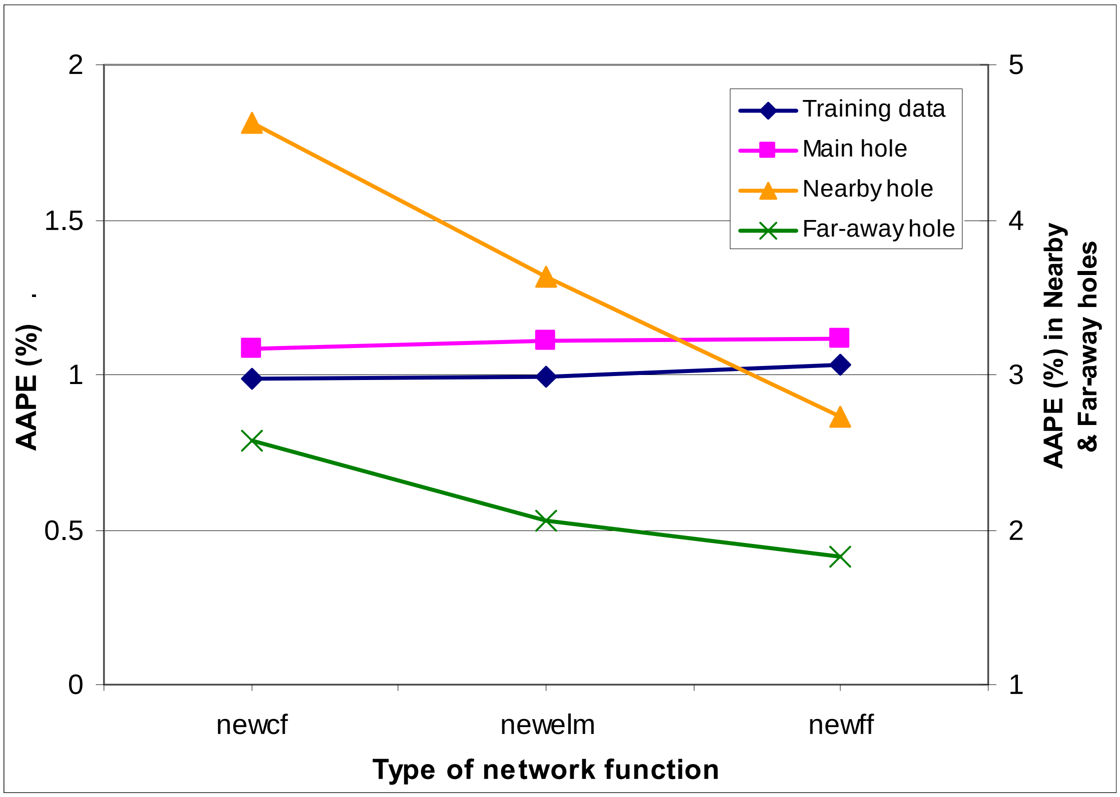


Figure 3.14: Effect of network function on average absolute percent relative error.

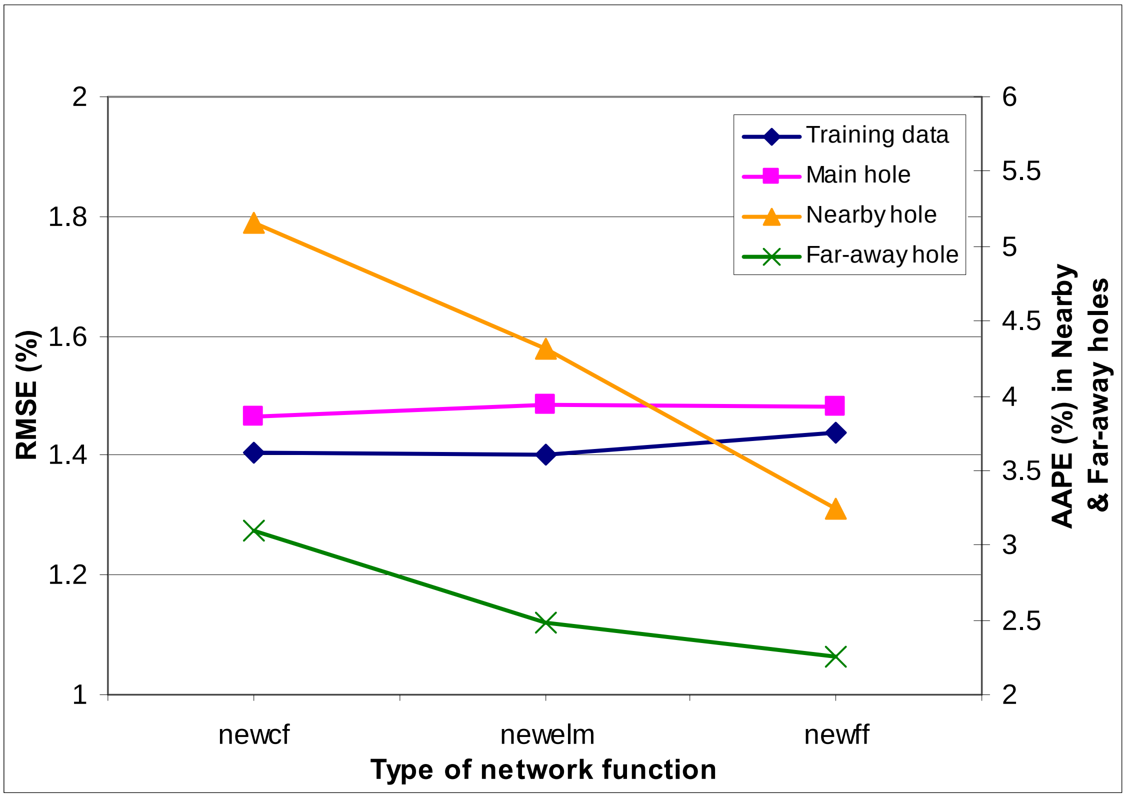


Figure 3.15: Effect of network function on root mean square error.

3.10.5 Determining the type of training algorithm

Using the same technique of trial and error, the optimal type of training algorithm is **Levenberg-Marquardt** since it has high correlation coefficient values as shown by figure 3.16 and lower error values as shown by figures 3.17 and 3.18.

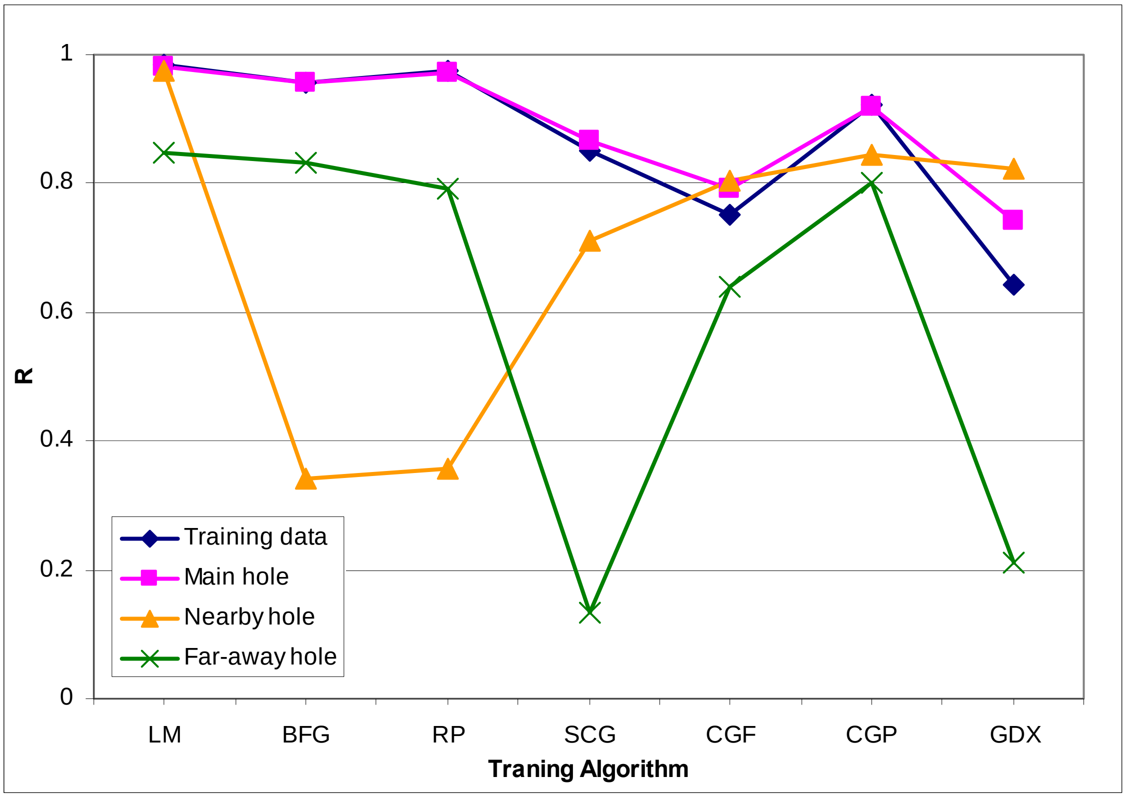


Figure 3.16: Effect of training algorithm on correlation coefficient.

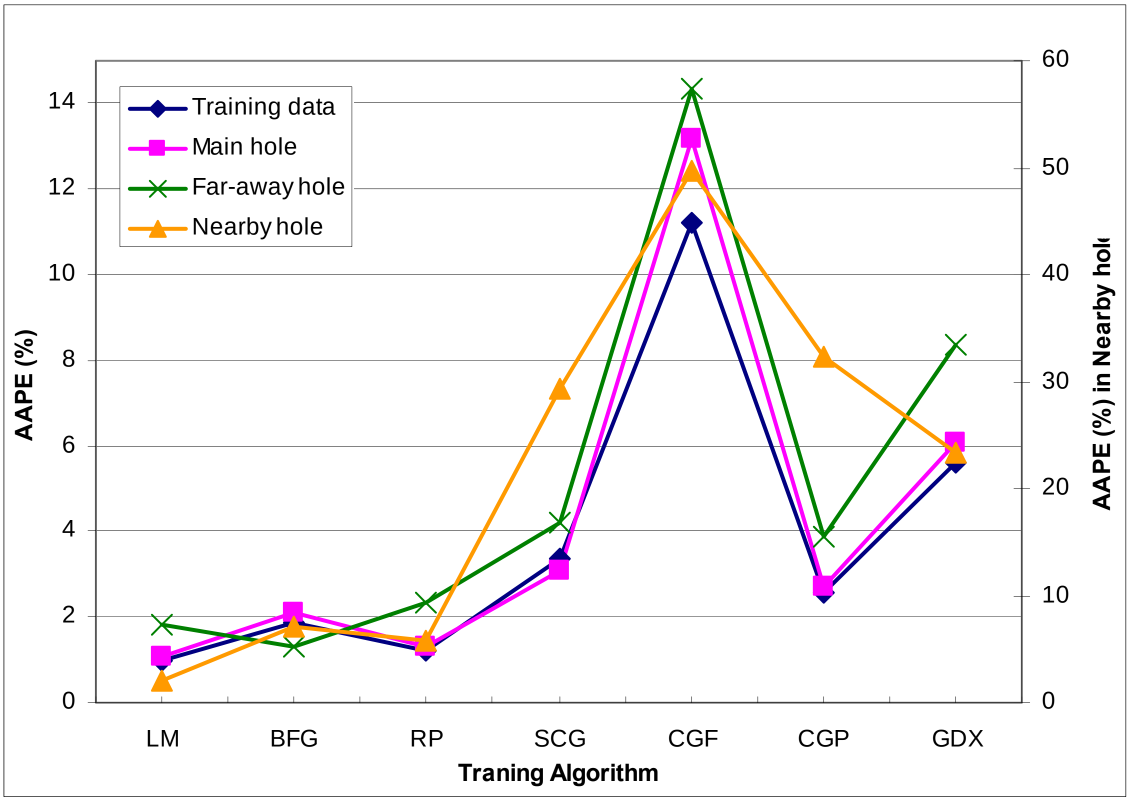


Figure 3.17: Effect of training algorithm on average absolute percent relative error.

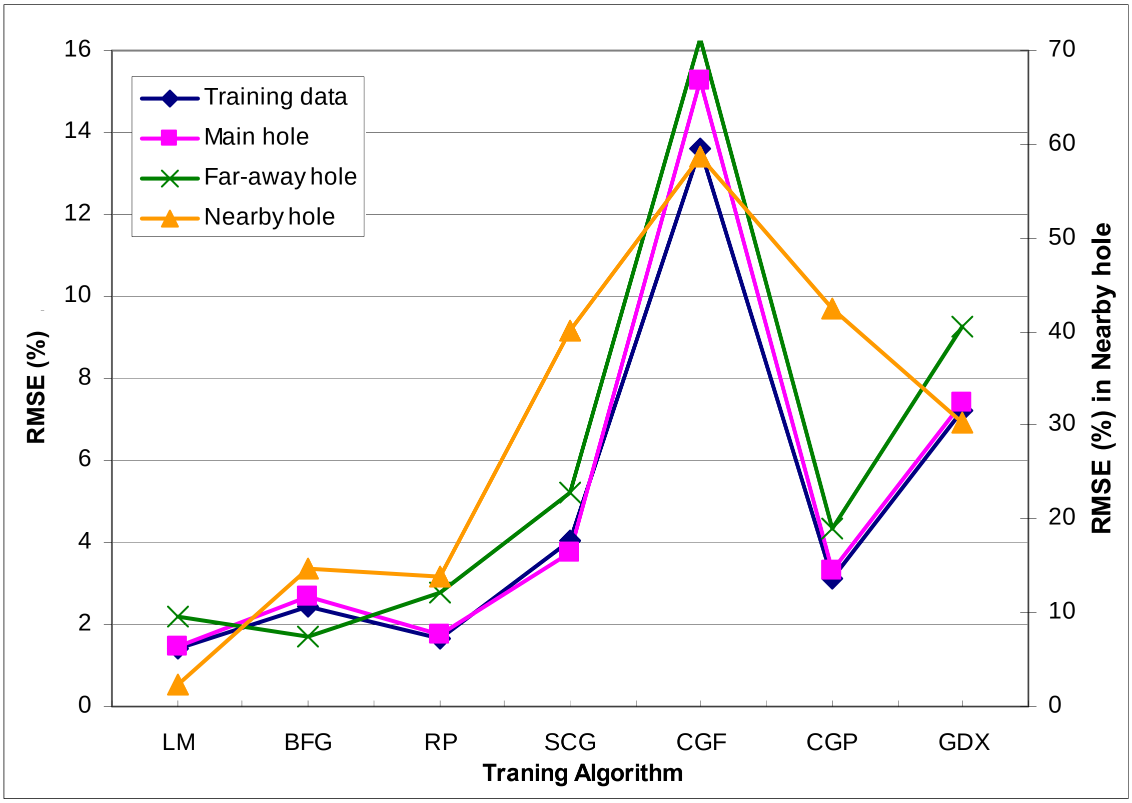


Figure 3.18: Effect of training algorithm on root mean square error.

CHAPTER 4

RESULTS AND DISCUSSION

In this chapter, we will discuss the need for predicting LWD density log by studying 4 possible scenarios. We will also present the results of predicting LWD density log using ANN technique.

4.1 Predicting LWD Density Using ANN:

Using the same approach that was discussed in the previous chapter, neural network models were created and used to predict the LWD density log. These models were created to study 4 possible scenarios. They are:

A. Correcting environmental and drilling artifacts in LWD density data.

B. Predicting LWD density log (sensor failure).

C. Predicting LWD density log in another nearby lateral.

D. Predicting LWD density log in a far-away well (same formation).

A similar procedure can be applied to other porosity logs like neutron. Therefore, for any porosity logs, ANN technique can be used to predict porosity measurements to be consistent with other wells.

A. Correcting environmental and drilling artifacts in LWD Density Data:

Environmental and drilling artifacts in LWD data was always an issue for petrophysicists especially LWD density log data since it has low DOI. These artifact data often received due to the effect of some factors (e.g. wash-out, bad sensor detection, tool vibration, or sliding) on the LWD density tool. Depending on the extent of these effects on the LWD density data and the importance of the well, these data need to be corrected before it used for formation evaluation. Three different methods will be discussed for solving this problem.

Method 1: Averaging technique.

Averaging method, which is considered the simplest method of all the three methods, uses two non-affected points before and after the bad data. After that, a simple arithmetic average is taken for the two points and this average is used in the bad data section. By applying the above method, the environmental and drilling artifacts in LWD data of figures 2.6 and 2.7 was corrected (figure 4.1) and the impact on calculated porosity could be significant as shown by figure 4.2.

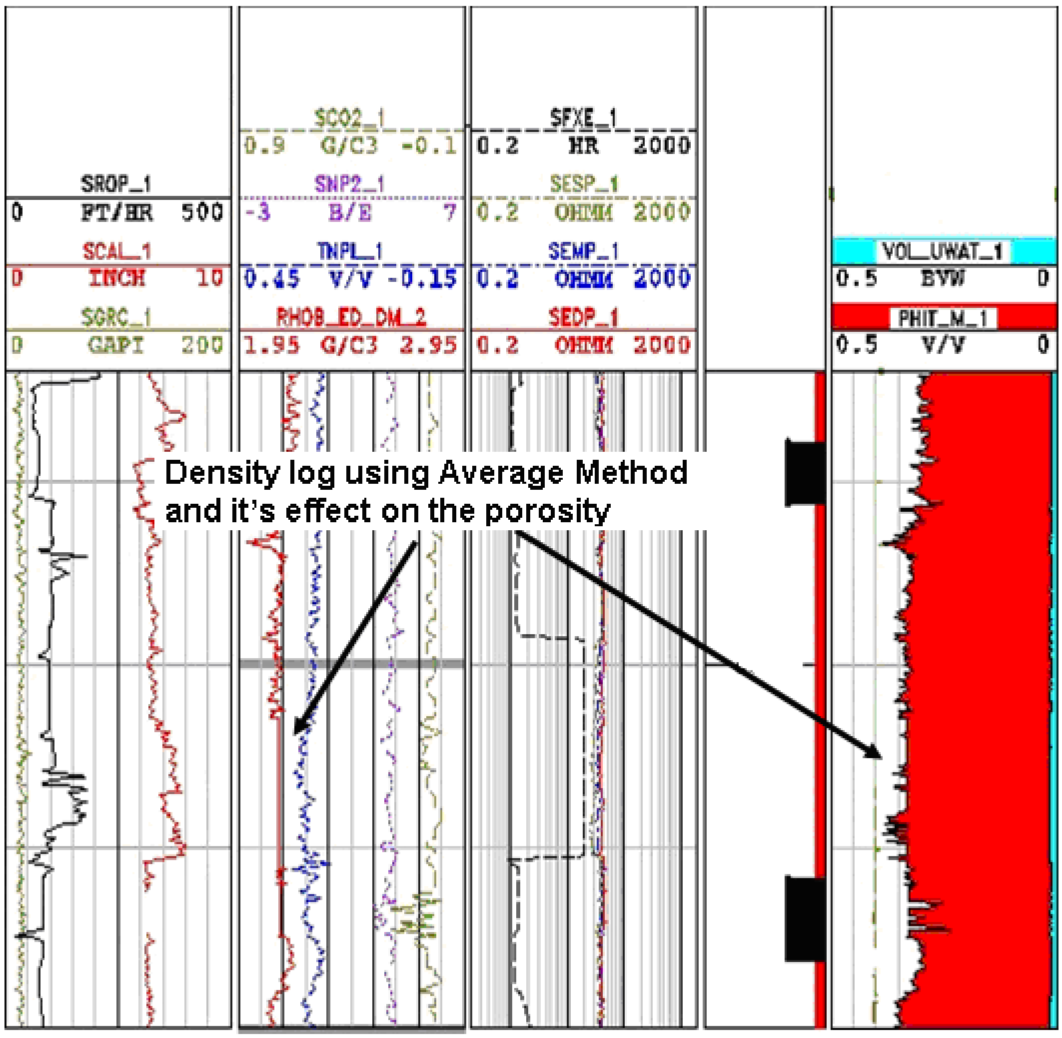


Figure 4.1: Incorrect data repair using average method.

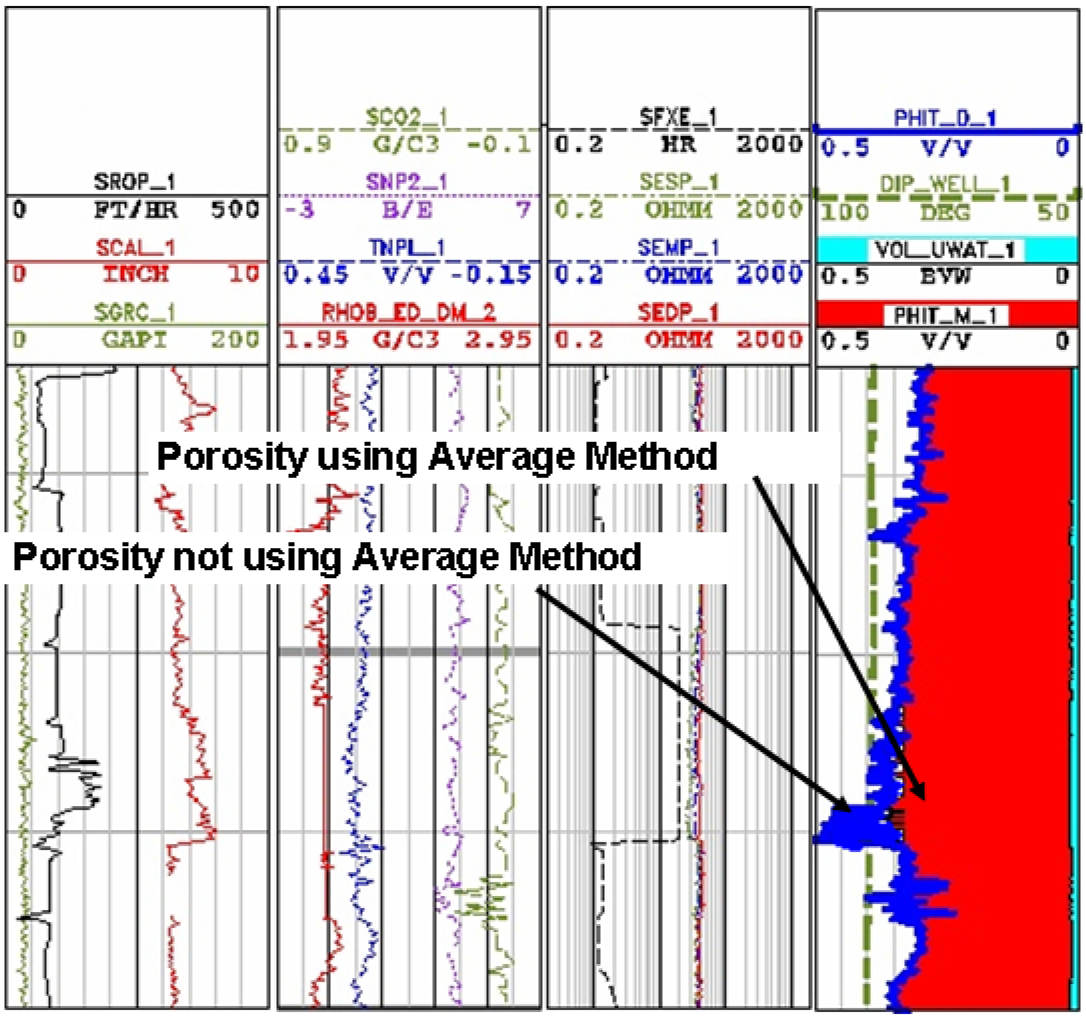


Figure 4.2: Comparison of porosity correction using average method. Using raw data directly can result in abnormally calculated porosity.

Method 2: neutron-density correlation method (NDCM).

Neutron (ϕ_n) density (ρ_b) correlation method uses the neutron density cross-plot to establish a correlation. After that, it uses that correlation to calculate the density log using the neutron log.

Using the density and neutron cross-plot (Figure 4.3), a correlation that fits the data is found. In this example, it is assumed to be a straight line. After that, an equation of this straight line was found as below:

$$\rho_b = 2.405 - 2.34(\phi_n - 0.15) \qquad (4.1)$$

Finally, the bad density data is re-calculated from neutron log by using the equation. By applying the above method, the artifacts in LWD data of figures 2.6 and 2.7 was corrected as shown by figures 4.4 and 4.5.

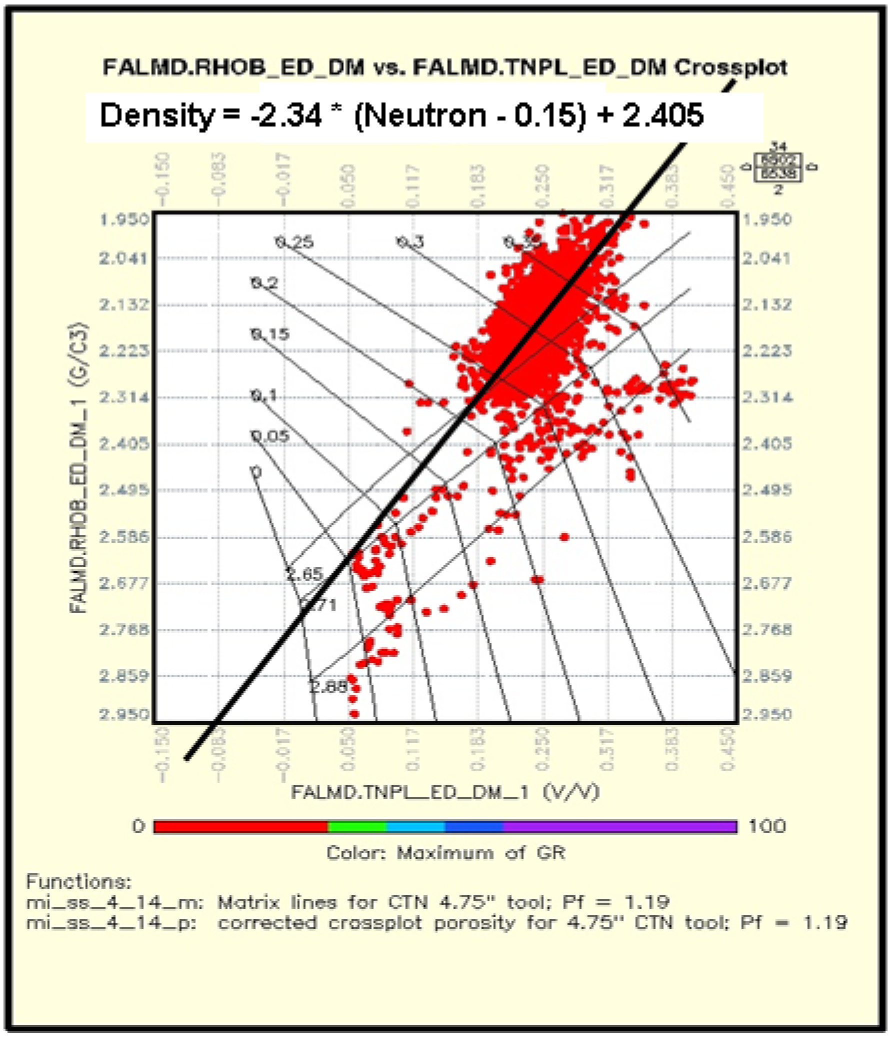


Figure 4.3: Neutron-density cross-plot.

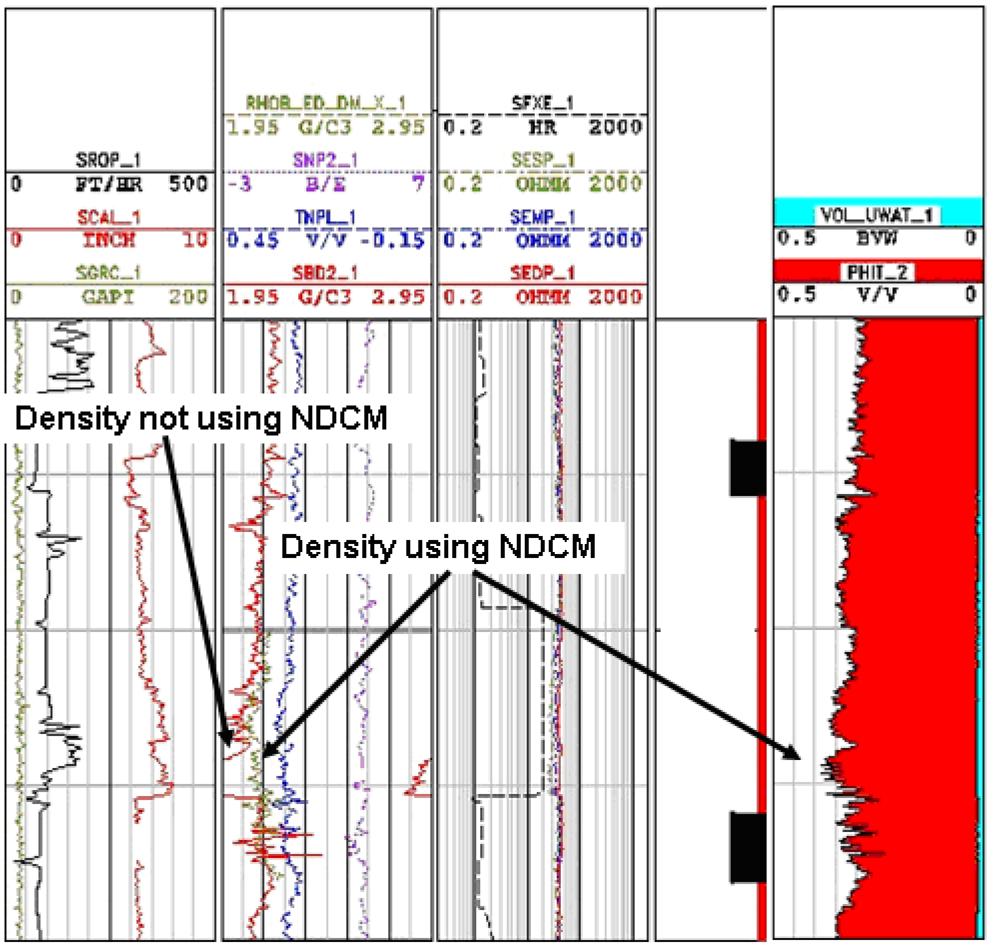


Figure4.4: NDCM and its effect on the density log and porosity calculation.

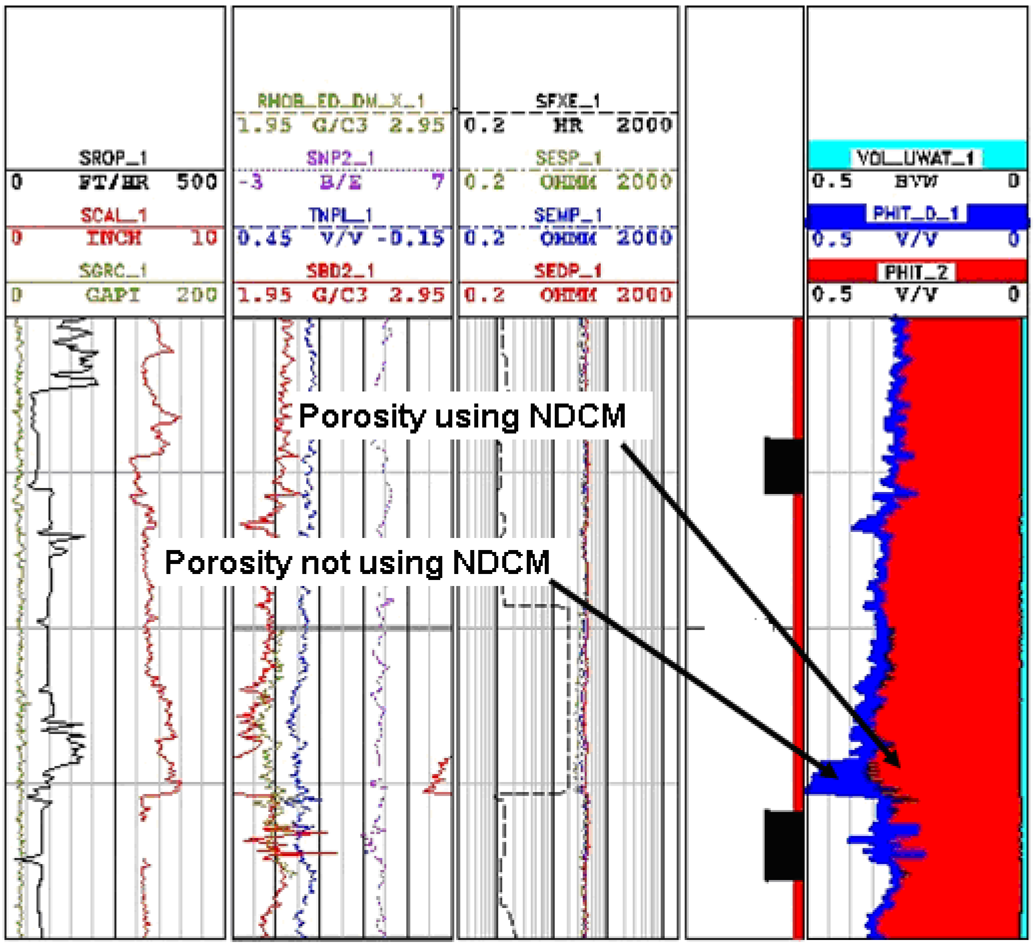


Figure 4.5: Comparison of porosity correction using NDCM. Using raw data directly can result in abnormally calculated porosity.

Method 3: Artificial Neural Network (ANN).

The short comings of the previous two methods are that the first one is simplifying the problem and that the second one is only taking neutron into account for recalculating the density log. ANN method not only uses the neutron log for recalculating the density log but it uses also gamma ray and resistivity which will make the results more realistic. In addition, it will add more confidence to results obtained.

An ANN model was constructed using LWD: GR, Neutron, and Resistivity (Rd, Rs) for training the LWD density log. The model consists of 4 input parameters, 10 nodes in the hidden layer, and 1 output parameter which is the density log. Selection of non-affected intervals was used (from the same hole) for training the neural network model (Figures 4.6 and 4.7) and testing it (Figure 4.8).

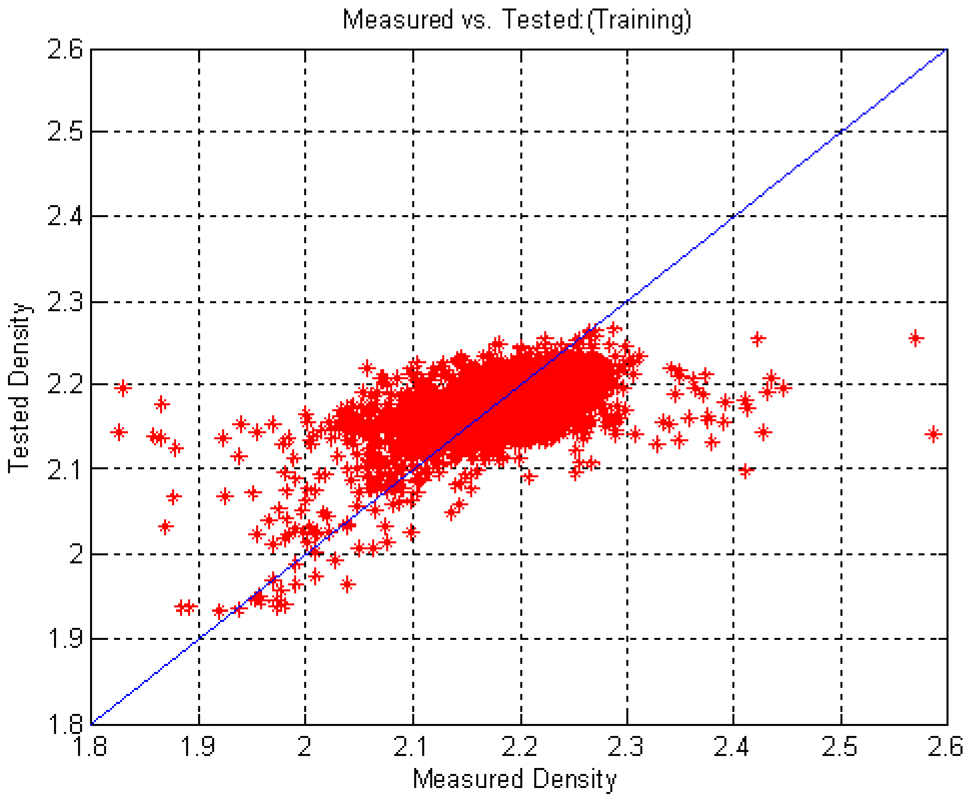


Figure 4.6: Simulated density vs. measured density cross-plot: case A (training).
It is used for training the neural network model. The LWD density data that are deviated from the 45 line are due to the effect of sliding on the data.

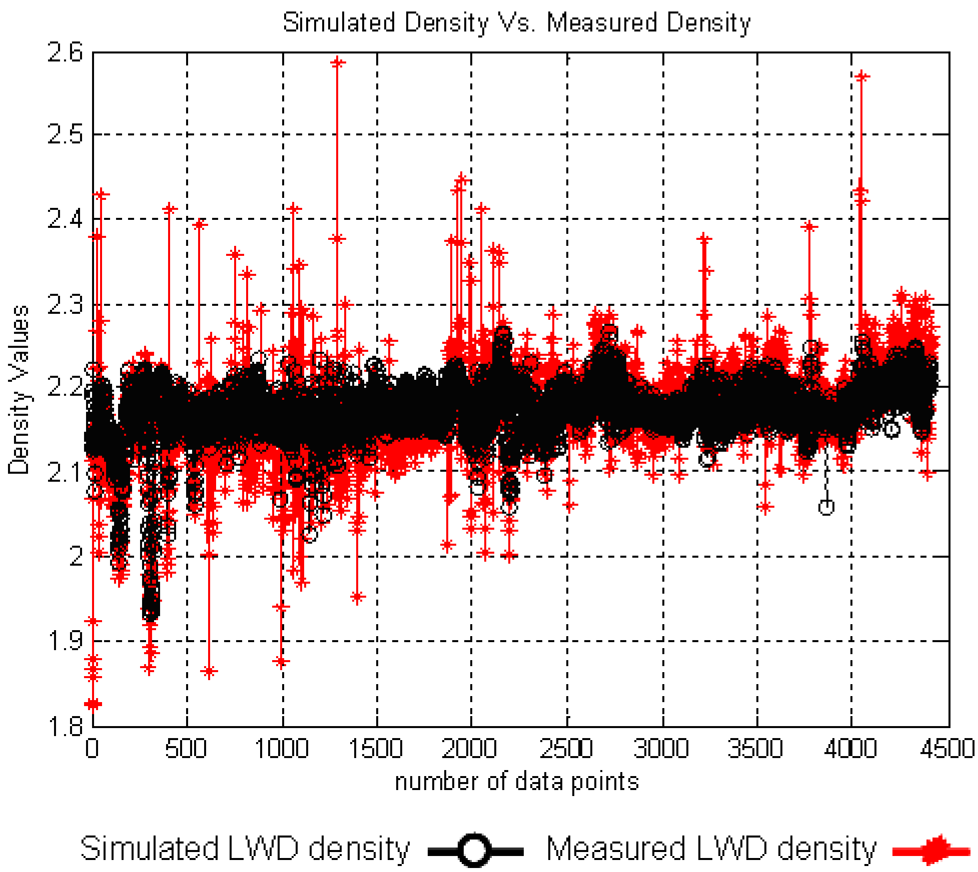


Figure 4.7: Simulated density and measured density vs. number of data pints: case A (training).

The simulated density data are in good agreement with the measured LWD density values.

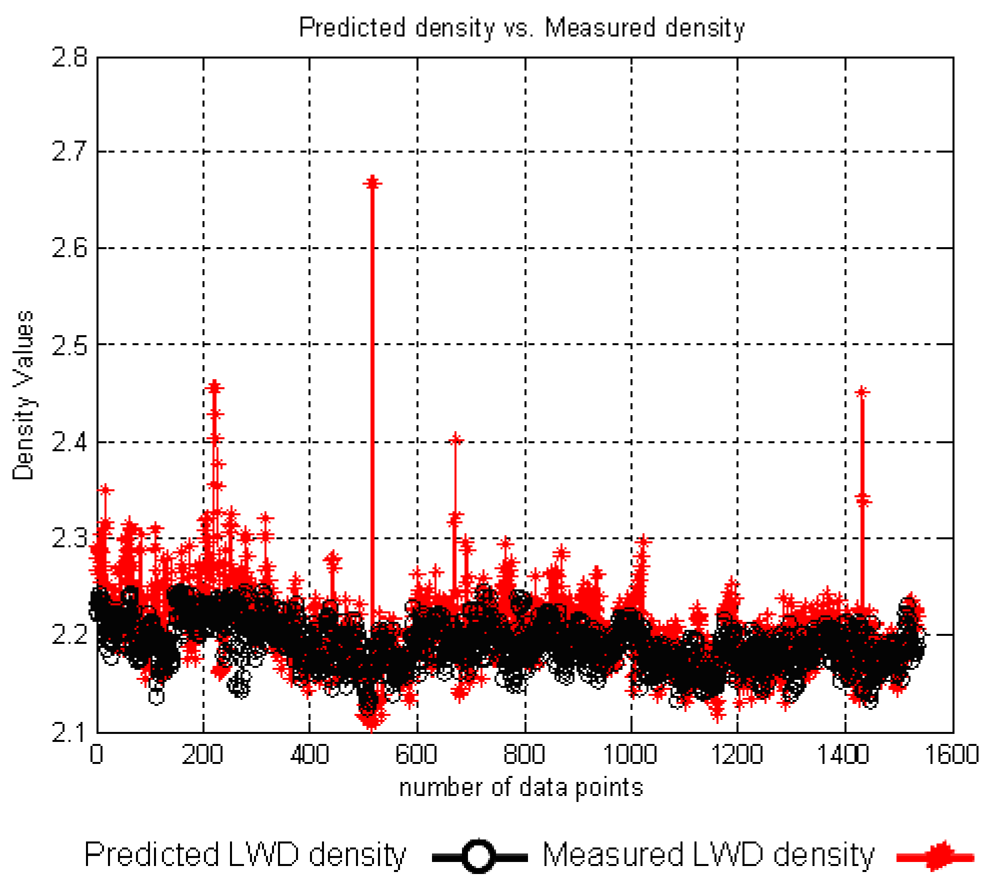


Figure 4.8: Predicted density and measured density vs. number of data points: case A (testing).
The predicted LWD density data are in good agreement with the measured values.

After we built a good confidence about the ANN model (error has good distribution as shown by figure 4.9), we are now able to predict the affected density data due to wash-out and sliding using LWD: GR, Neutron, and Resistivities. Results are showing in figure 4.10.

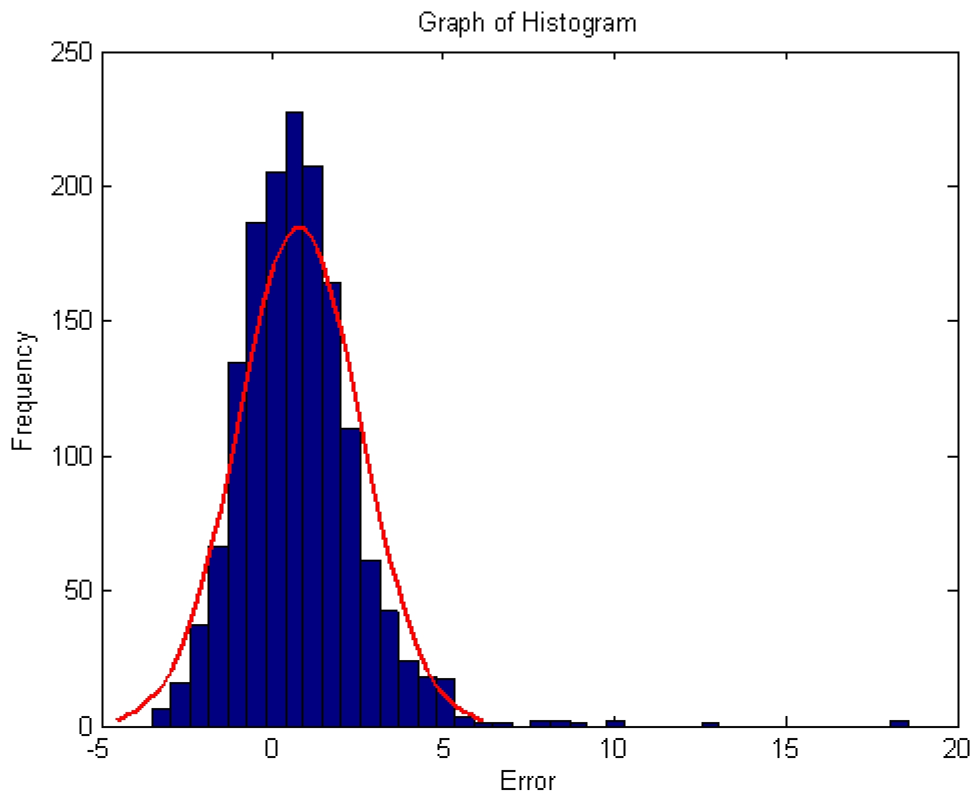


Figure 4.9: Frequency histogram for error calculation: case A (testing).

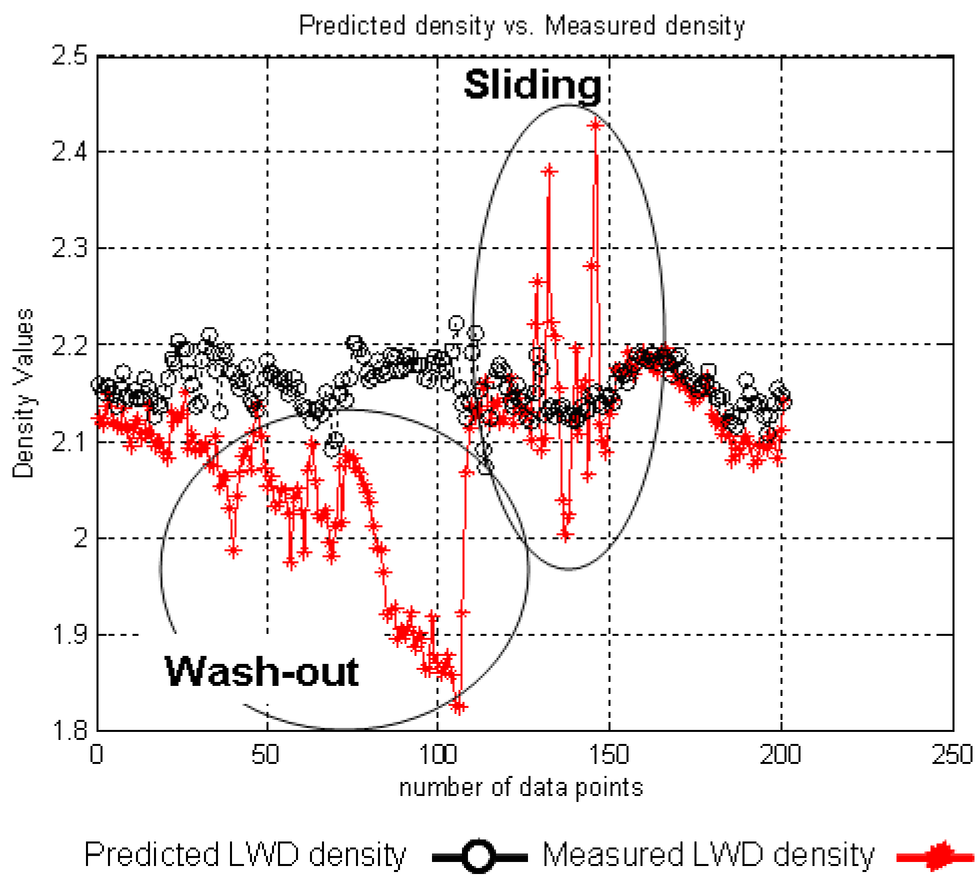


Figure 4.10: Predicted the targeted density and affected measured density vs. number of data points.
The predicted density data are in good agreement with the non-affected measured LWD density log.

B. Predicting LWD density log (sensor failure):

In some situations, one or more LWD sensors may fail resulting in loss of LWD data. In this case, we have the following options:

1. Pull the whole BHA out of hole and replace the LWD tool with a new one (it is our policy to always have a back-up LWD tool on location).

2. Continue drilling with the rest of the LWD sensors until a bit trip. This option saves rig time, but the missed log data needs to be filled by prediction from other available data.

Option 2 is always desirable because of saving of rig time. This is always the case when the LWD density tool sensors failed. When the LWD density tool fails, GOC continue drilling using the neutron log. To take advantage of Option 2, the missed log data needs to be predicted in real time for better well placement. There are several methods that can be used for log predicting depending on the data availability. In this thesis, however, we will use the artificial neural network model for prediction density log.

Missing Data Prediction: An Example

While drilling a horizontal well, we assumed that the density logging tool failed close to TD. Decision was made in real time to continue the horizontal drilling to TD hoping that data in the LWD tool memory was usable, or the missed data can be predicted using existing logs in the same reservoir. After the tool surfaced, it was discovered that data in tool memory was not usable. The missed density data had to be predicted using the data available at the top intervals (before the density tool failed).

An ANN model was constructed using the same methodology that was discussed in chapter 3. The model consists of 4 input parameters, 10 nodes in the hidden layer, and 1 output parameter which is the LWD density log. LWD: GR, Neutron, and Resistivity were used to train and test the data above the depth at which the density log sensor failed. Figures 4.11 to 4.13 illustrate the results of training and testing the model.

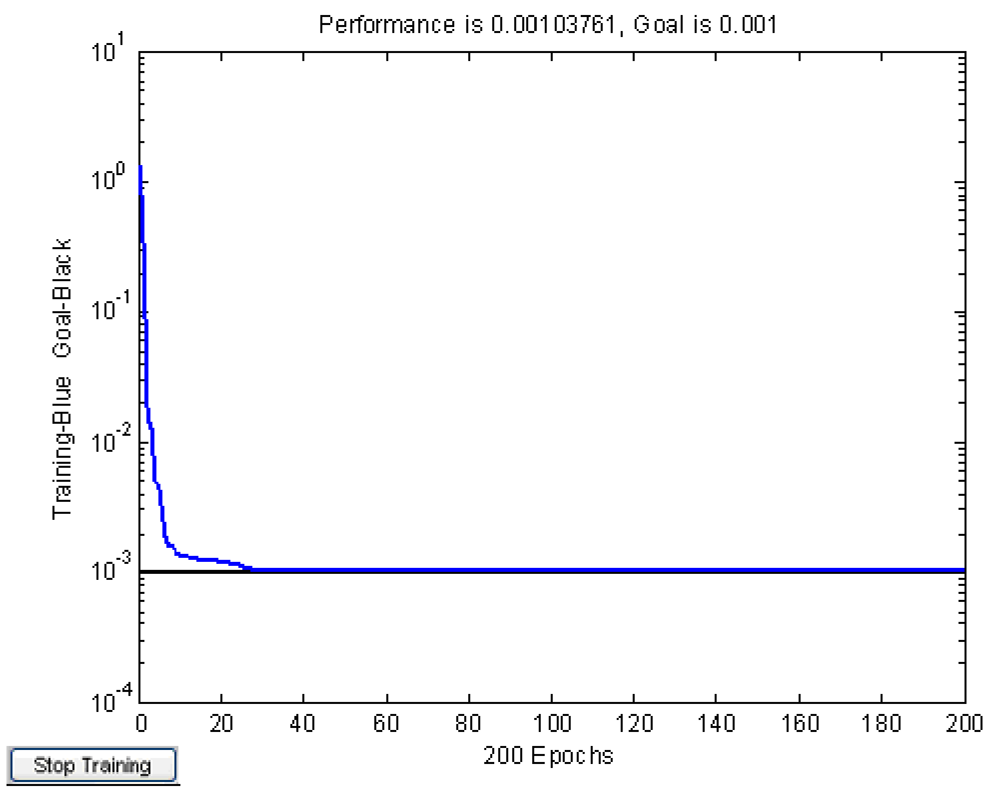


Figure 4.11: Performance Curve.
Training matches the goal that was set at the beginning at 0.001 error. This means that the neural network model that was generated is able to predict the LWD density within that range.

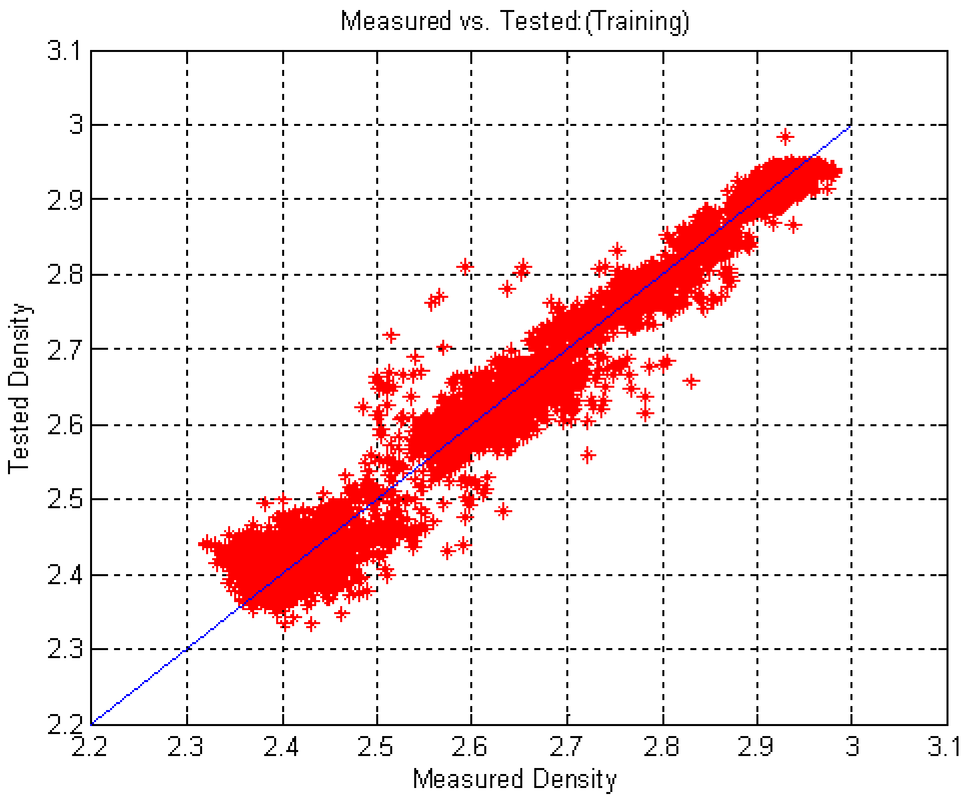


Figure 4.12: Simulated density vs. measured density cross-plot: case B (training).

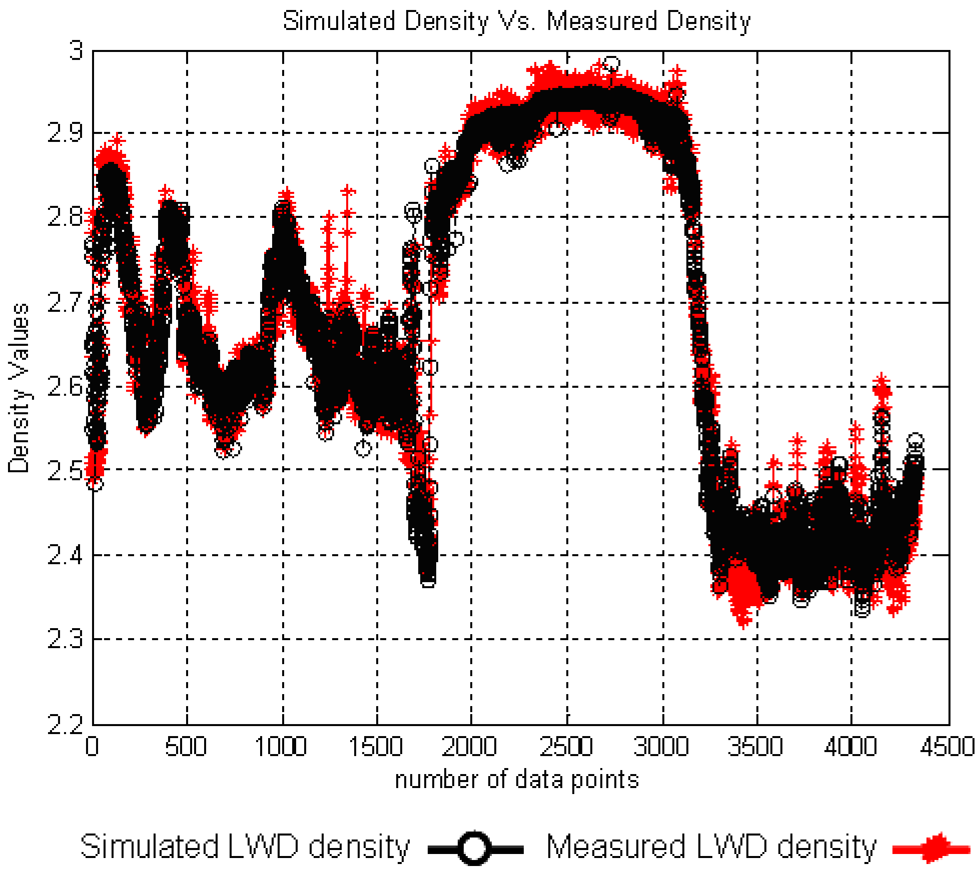


Figure 4.13: Simulated density and measured density vs. number of data points: case B (training).

After the weight of the neural network adjusted in the training phase, the model was applied to predict the missed log data of about 900’ (figures 4.14 and 4.15). Using the model and the other available data (GR, Resistivity, and Neutron) below the depth at which the density tool failed, we were able to predict the density log with high accuracy (figure 4.16). Now, a complete suite of logs can be used for detailed formation evaluation.

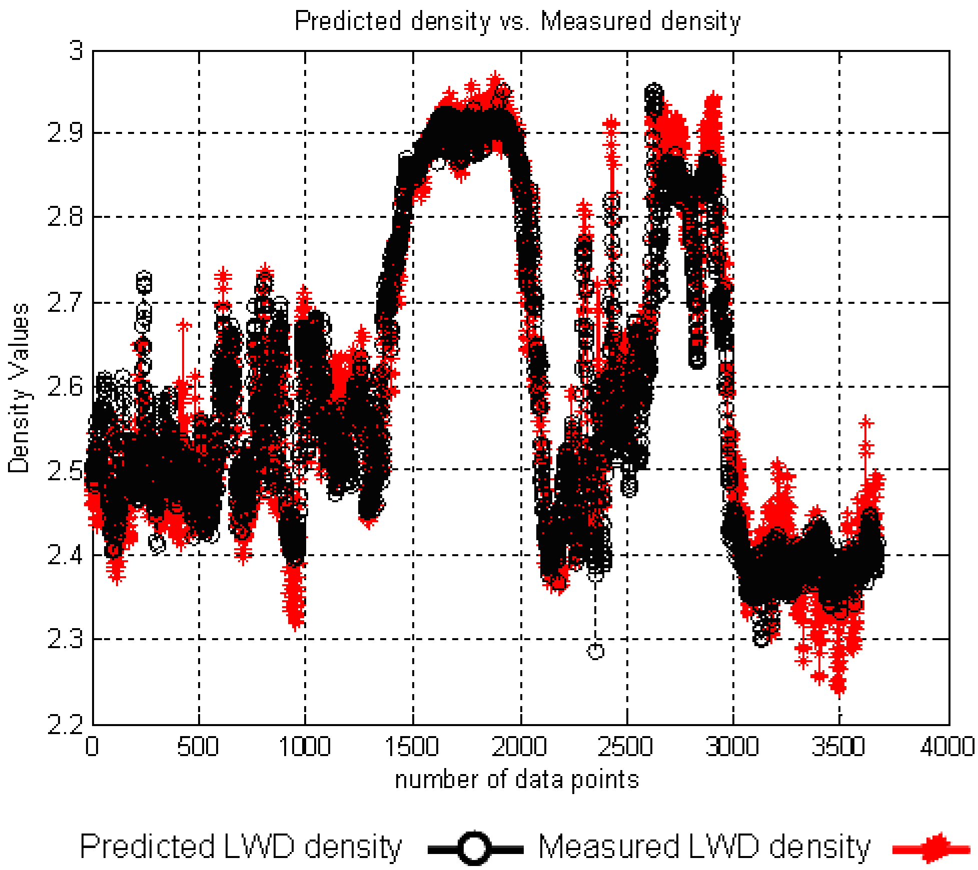


Figure 4.14: Predicted density and measured density vs. number of data points: case B (testing).

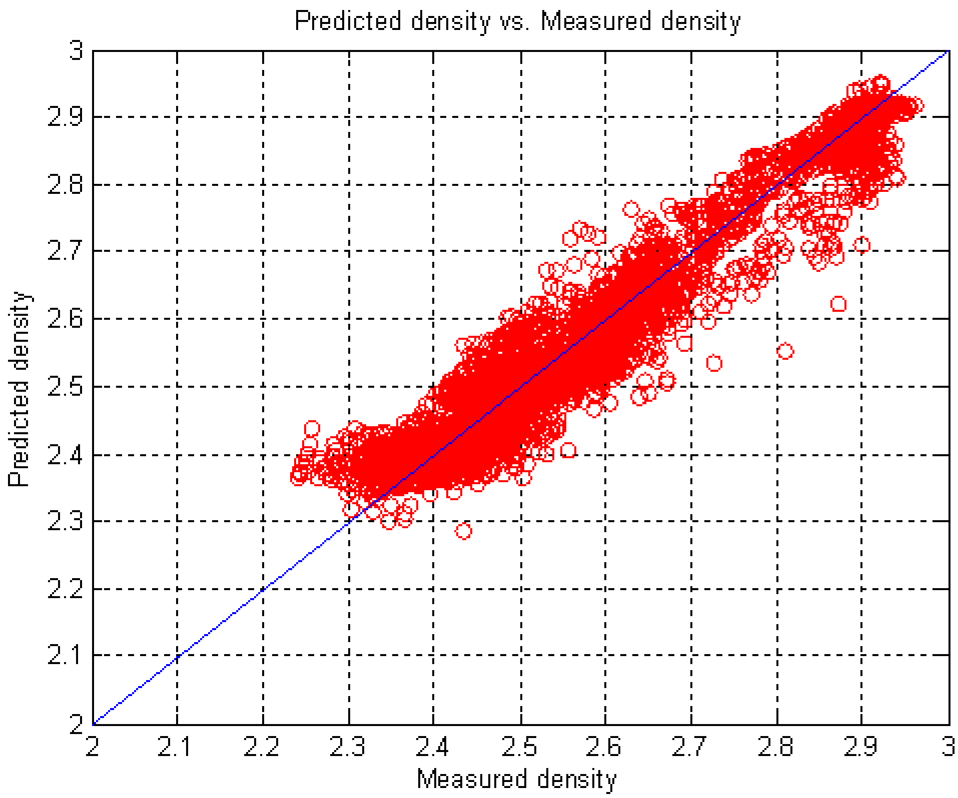


Figure 4.15: Predicted density vs. measured density cross-plot (testing).

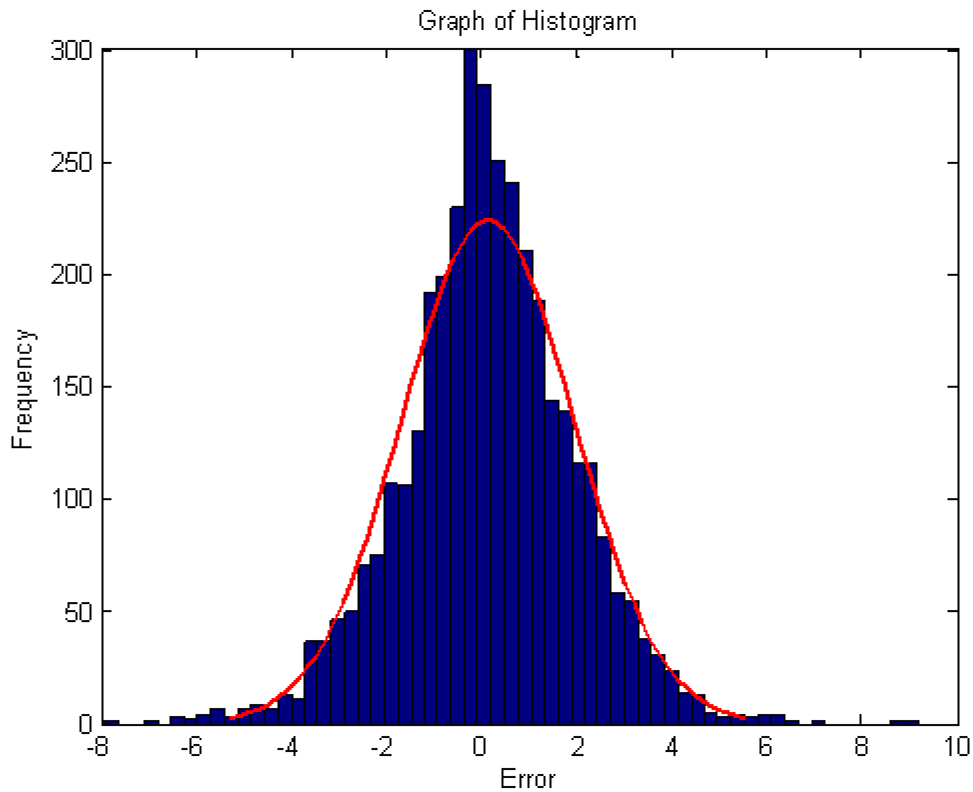


Figure 4.16: Frequency histogram for error calculation: case B.

C. Predicting LWD density log in another nearby lateral:

Neural network models can also be used to predict data in a nearby lateral using original hole (mother bore) data for training the model. This can help to reduce some of the cost of logging by dropping running LWD density without stabilizer in case we side-track with small hole.

The same ANN model that was used in the previous example was used to predict the density log in a nearby lateral of the same well. The only exception is that in this example, we used all the mother bore data for training. Figures 4.17 to 4.20 show the results of prediction compared to the measured density log for training and testing. Error has good distribution as shown by figure 4.21.

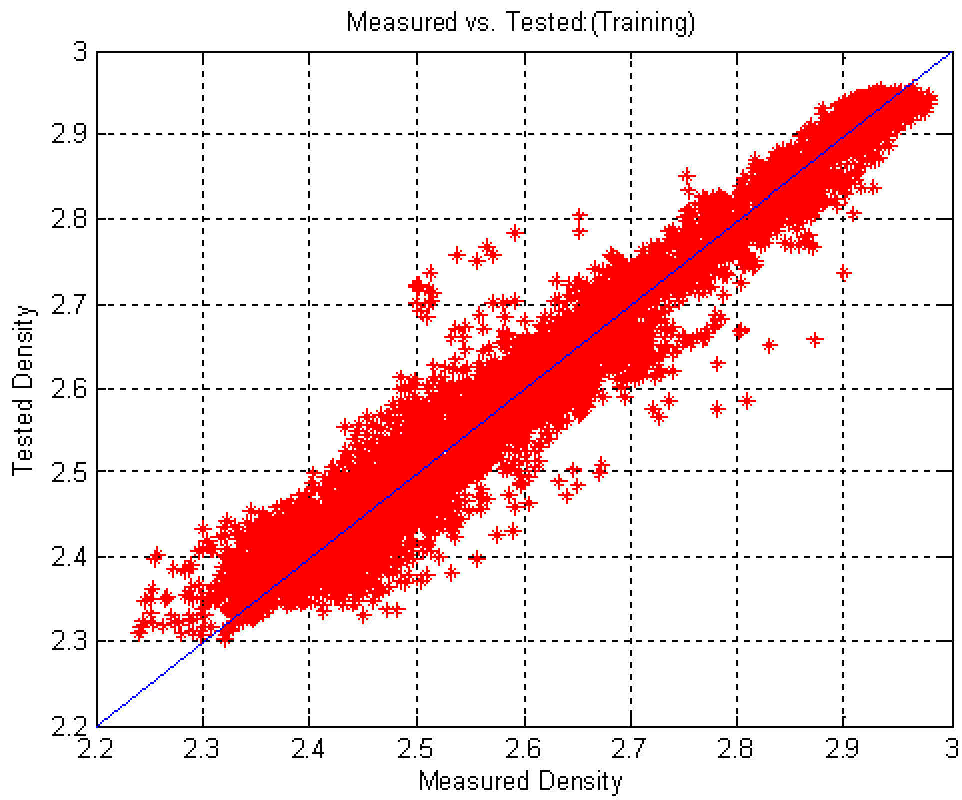


Figure 4.17: Simulated density vs. measured density cross-plot: case C (training).

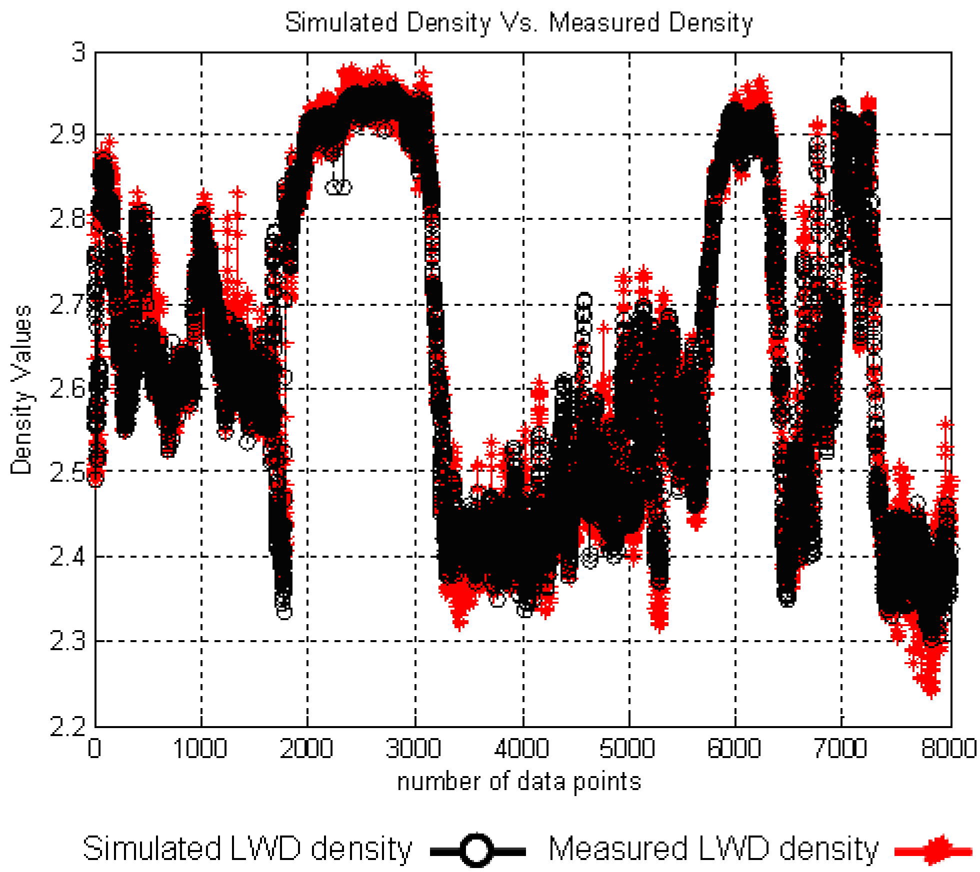


Figure 4.18: Simulated density and measured density vs. number of data points: case C (training).

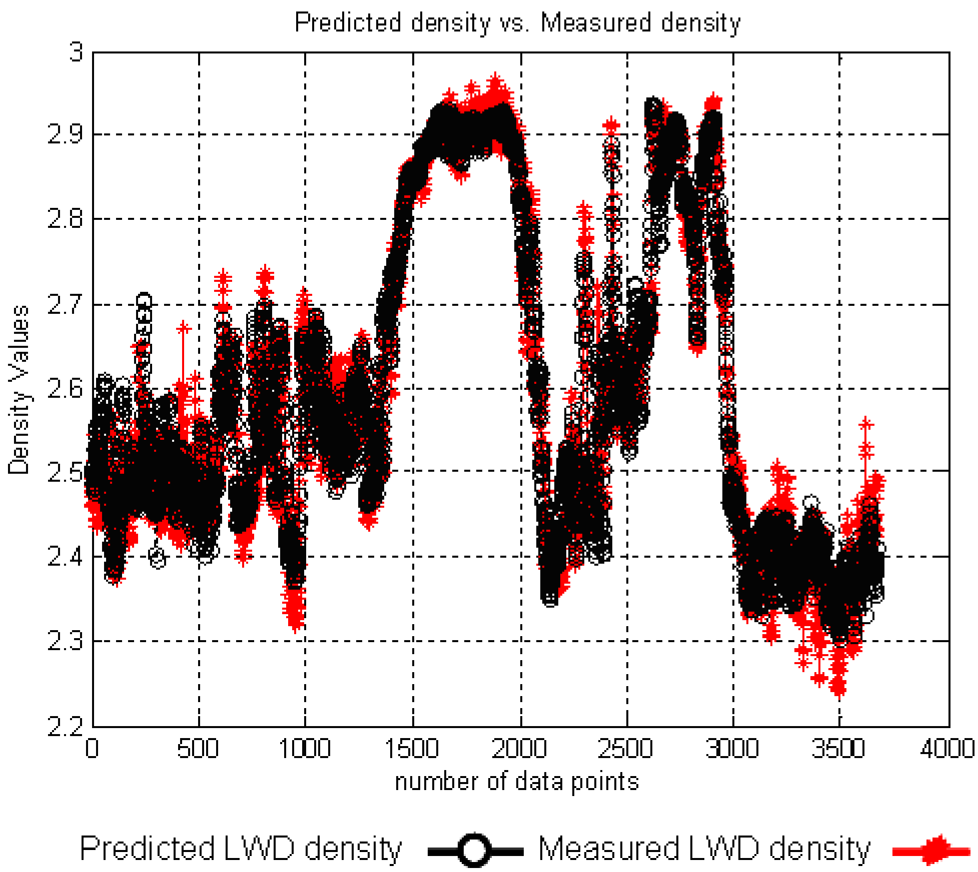


Figure 4.19: Predicted density and measured density vs. number of data points: case C (testing).

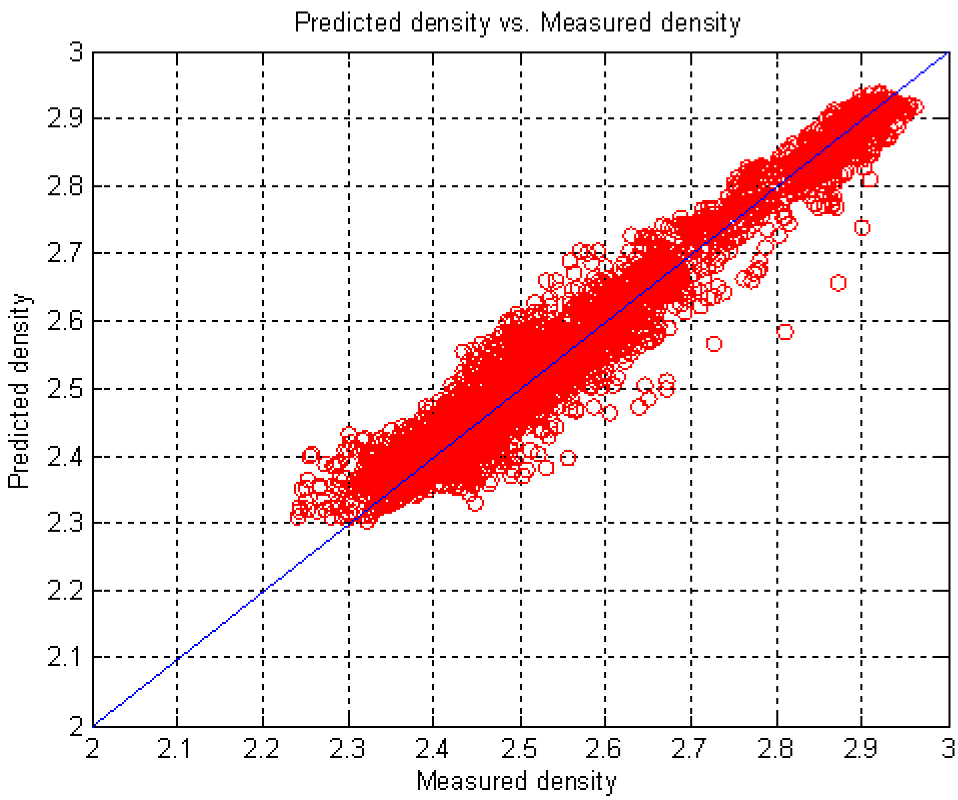


Figure 4.20: Predicted density vs. measured density cross-plot: case C (testing).

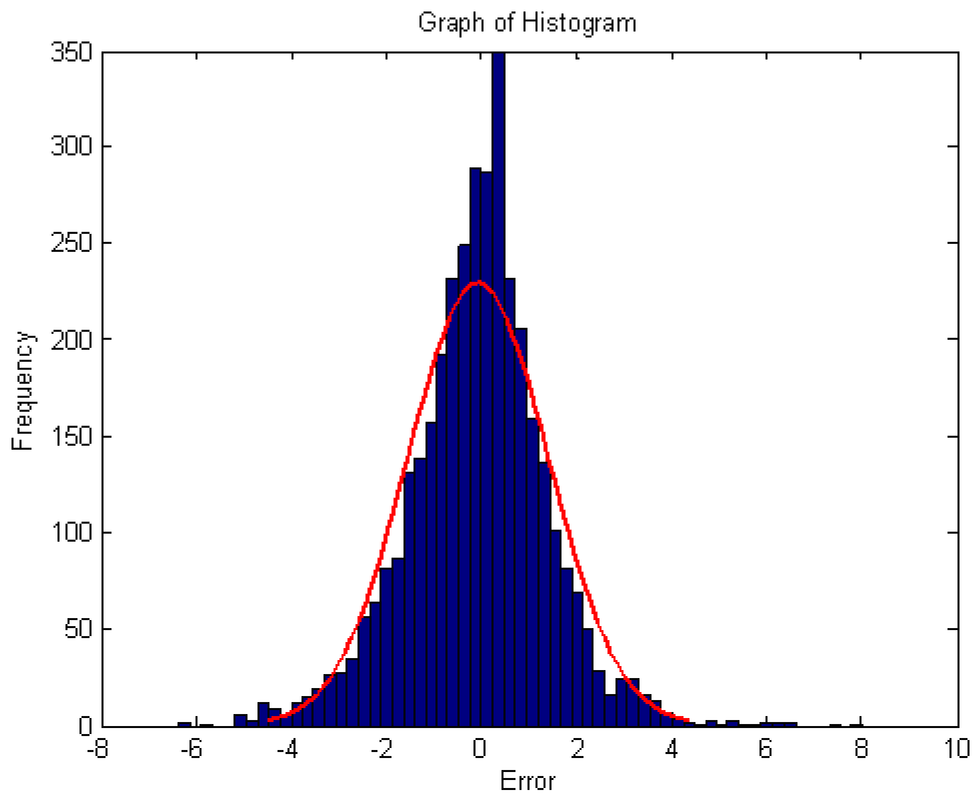


Figure 4.21: Frequency histogram for error calculation: case C (testing).

The model program can reproduce itself with good confidence. Therefore, it was applied to predict the complete data of the nearby lateral (Figures 4.22 and 4.23) using the model and the other available data (GR, Resistivity, and Neutron) of the target lateral. The predicted density log has high accuracy as shown by figure 4.24). Now, a complete suite of logs can be used for detailed formation evaluation.

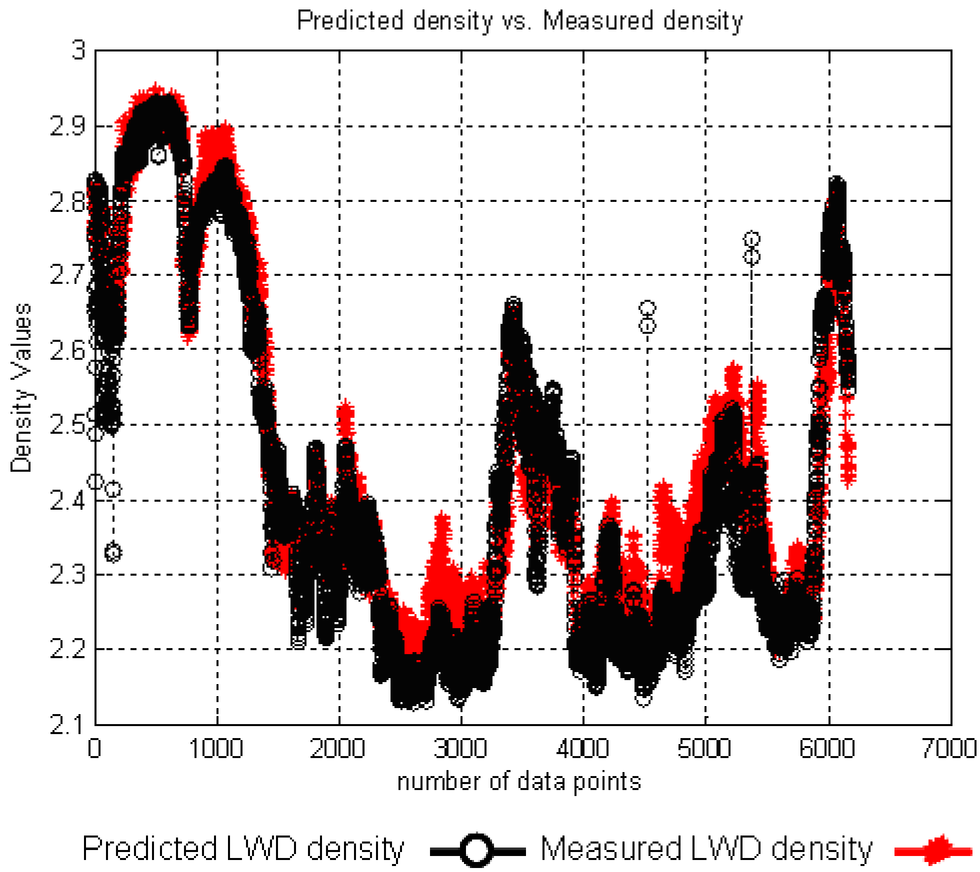


Figure 4.22: Predicted density and measured density vs. number of data points: case C (target).

The predicted density has good agreement with the measure LWD density.

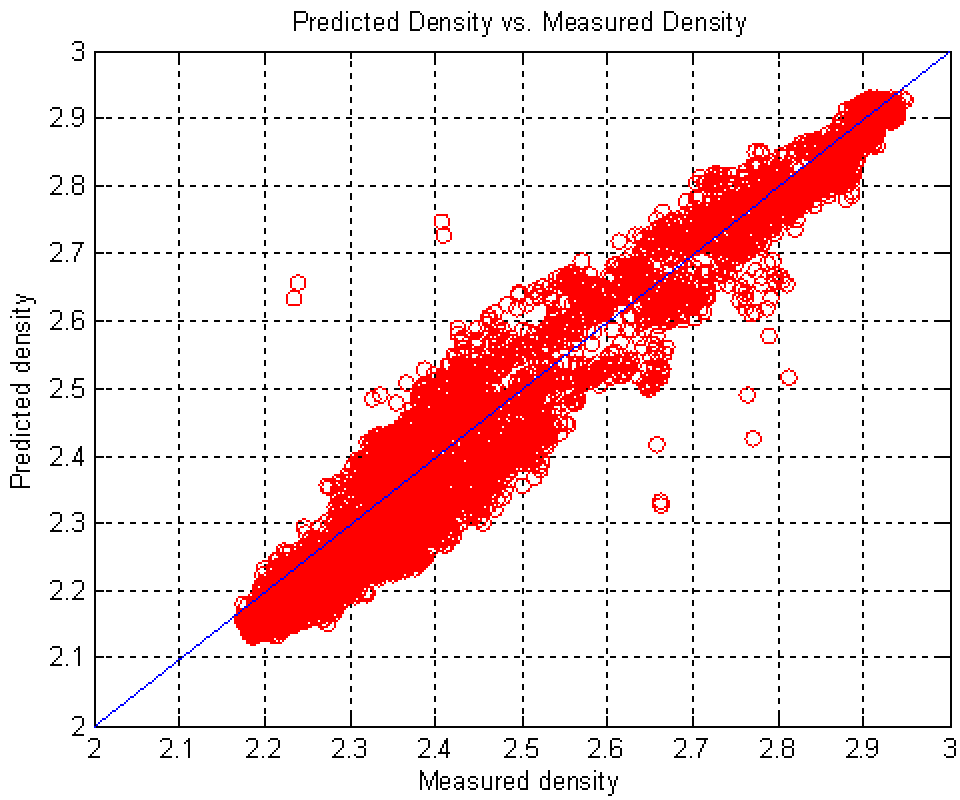


Figure 4.23: Predicted density vs. measured density cross-plot: case C (target).

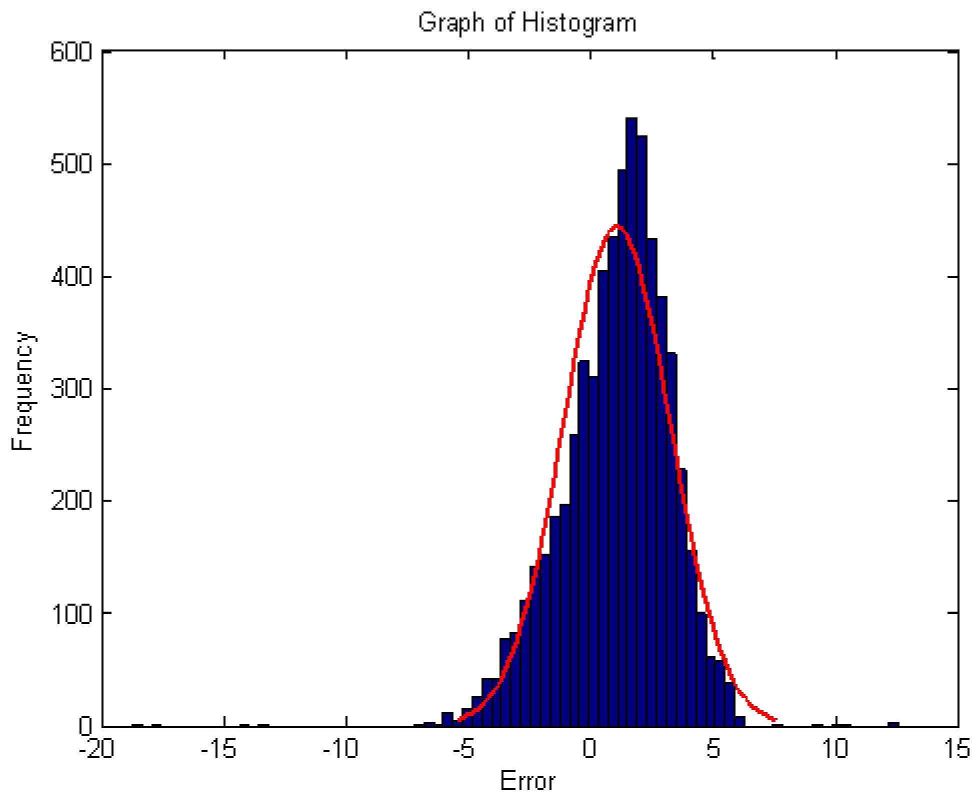


Figure 4.24: Frequency histogram for error calculation: case C (target).

D. Predicting LWD density log in a far-away well (same formation):

The same model, which was generated in part C, was also tested in a well that is far away from original well but it was in the same formation. We assumed that we drilled a well in a new area and we had to drill with a small hole because we encountered un-expected gas kick and we had to isolate that formation using casing. Thus, we were unable to run the density tool with stabilizer. Therefore, we decided to drop it from the logging program and predict it using ANN. The predicted results were very close to the measured values. Figures 4.25 to 4.27 shows the results of predicting LWD density log.

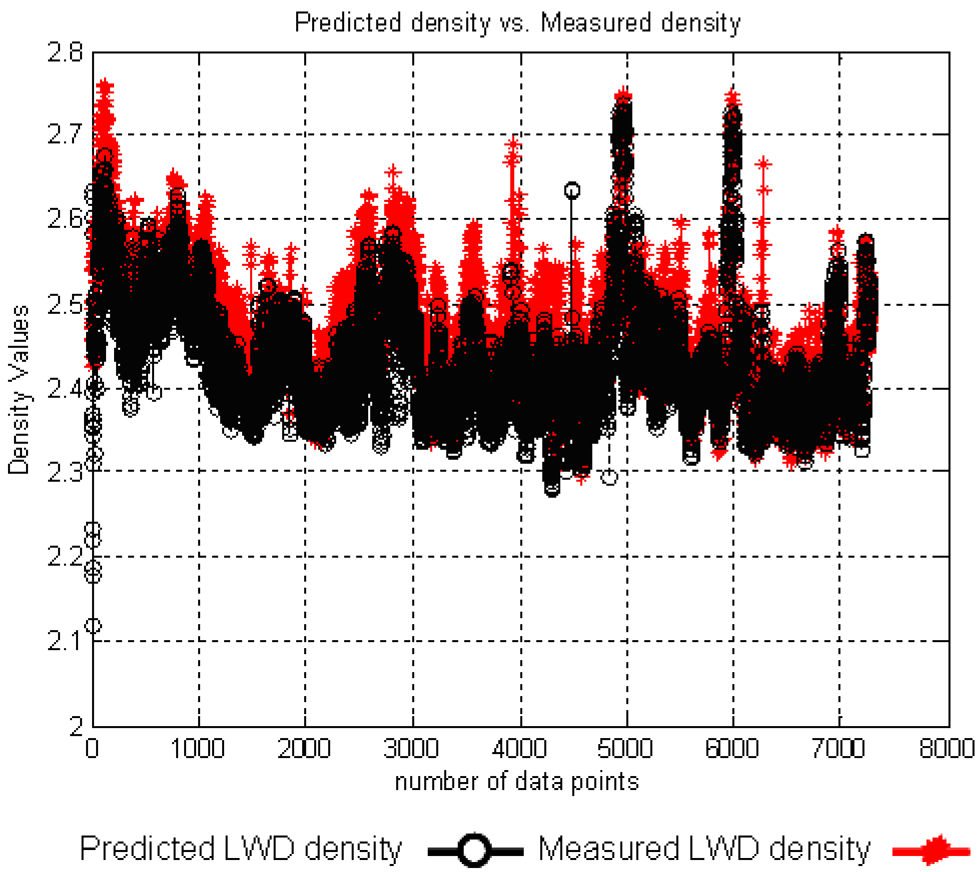


Figure 4.25: Predicted density and measured density vs. number of data points: case D (target).

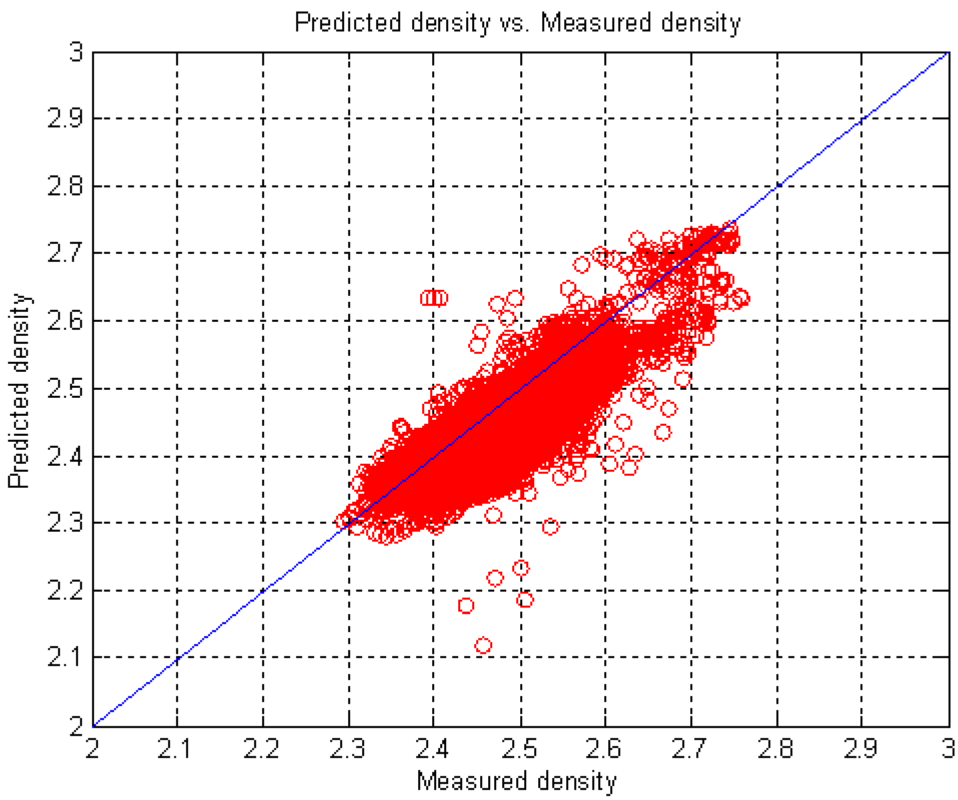


Figure 4.26: Predicted density and measured density vs. number of data points: case D (target).

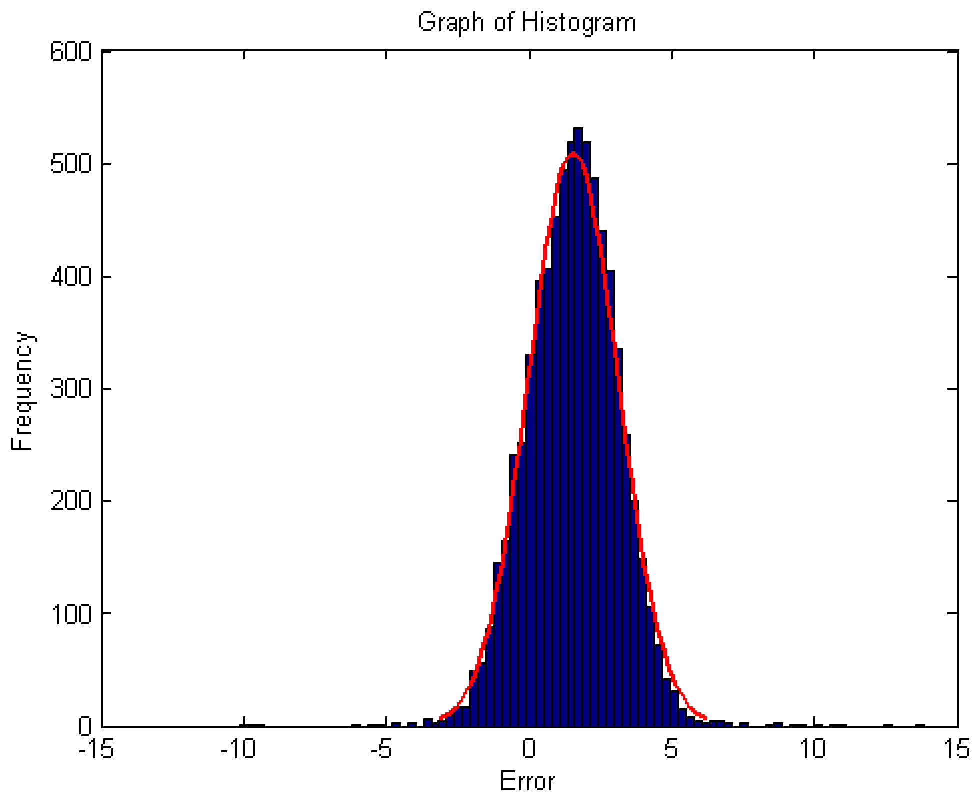


Figure 4.27: Frequency histogram for error calculation: case D (target).

4.2 Statistical Error Analysis:

Statistical error analysis was performed to evaluate the predicted log measurements (LWD density log) using ANN method by comparing the predicted results with the actual measurement of the tool. The statistical error methods that was studied are: average percent relative error, average absolute percent relative error, minimum and maximum absolute percent error, root mean square error, standard deviation of error, and the correlation coefficient.

In the 4 scenarios that were studied in the previous section (4.1), statistical error analysis is presented in table 4.1 which includes only 3 of them (scenario A shouldn't be used since the actual measurements are affected by sliding and borehole washout)

TABLE 4.1: Statistical error analysis:

Scenario	R	MaxErr	MinErr	AAPE	APE	RMSE	STDE
B	0.97	9.18	1.48E-03	1.38	0.13	1.81	1.80
C	0.98	10.29	3.56E-05	1.63	-0.05	2.07	2.07
D	0.83	10.02	2.17E-04	1.71	1.36	2.12	1.63

For more information regarding the acronym and the mathematical equations, please refer to the Appendix.

CHAPTER 5

CONCLUSIONS

- Wells drilled with geosteering could be completed in shorter times by eliminating trips to repair or replace LWD tools.

- LWD data may have bad readings due to factors such as hole wash-out, bad sensor detection, tool vibration, and sliding while changing azimuth or inclination angle.

- Environmental and drilling artifacts in LWD data needs to be corrected before it is used for formation evaluation.

- In the case of the complete loss of LWD density data on a well due to tool or sensor failure, the missed LWD density data can be predicted from other available logs for better well placement and to have a meaningful and consistent formation evaluation across the whole reservoir.

- In some cases, running LWD density tool with stabilizer is not an option due to hole size limitation. Therefore, it is recommended not to run the LWD density tool and predict the density data instead.

- Artificial neural network method shows a good estimation process that worked within the expectation.

- To have the optimal neural network model, a trial and error analysis is required for evaluation.

- ANN technique could be applied to other porosity logs, like neutron using similar procedures, to have consistent porosity measurements across the whole reservoir.

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APPENDIX

Correlation Analysis:

Before you fit a function to model the relationship between two measured quantities, it is a good idea to determine if a relationship exists between these quantities.

Correlation is a method for establishing the degree of probability that a linear relationship exists between two measured quantities. When there is no correlation between the two quantities, then there is no tendency for the values of one quantity to increase or decrease with the values of the second quantity.

Correlation Coefficients Matrix [10]:

The correlation coefficient matrix represents the normalized measure of the strength of linear relationship between variables. **r = corrcoef(X)** returns a matrix **r** of correlation coefficients calculated from an input matrix **X** whose rows are observations and whose columns are variables. The matrix **r = corrcoef(X)** is related to the covariance matrix **C = cov(X)** by:

$$r\,(i,j) = \frac{C(i,j)}{\sqrt{C(i,i)C(j,j)}}$$

The covariance function is defined as:

$$Cov(x_1, x_2) = \mathrm{E}[(x_1 - \mu_1)(x_2 - \mu_2)]$$

where **E** is the mathematical expectation and $\mu_i = E\chi_i$. The covariance removes the mean from each column before calculating the result.

A matrix of correlation coefficients for a data matrix (where each column represents a separate quantity) will be produced. The correlation coefficients range from -1 to 1, where:

- Values close to 1 suggest that there is a positive linear relationship between the data columns.
- Values close to -1 suggest that one column of data has a negative linear relationship to another column of data (anti-correlation).
- Values close to or equal to 0 suggest there is no linear relationship between the data columns.

Statistical Error Analysis [6]:

The statistical error analysis are mathematical equations used to evaluate the quality of LWD density prediction which include: average percent relative error, average absolute percent relative error, minimum and maximum absolute percent error, root mean square error, standard deviation of error, and the correlation coefficient.

1. Average Percent Relative Error (APE):

It is a measure of relative deviation from the experimental data. Mathematically:

$$E_r = \frac{1}{n}\sum_{i=1}^{N} E_i$$

Where Ei is the relative deviation of an estimated value from an actual value:

$$E_i = \left[\frac{\rho_m - \rho_p}{\rho_m}\right] \times 100, \qquad i = 1, 2, 3 \ldots n$$

2. Average Absolute Percent Relative Error (AAPE):

It is a measure of the relative absolute deviation from the actual values. Mathematically:

$$E_a = \frac{1}{n}\sum_{i=1}^{n}|E_i|$$

This error analysis considered to be one of the main criterions in statistical error analysis that was used to select the optimal neural network model and to evaluate the accuracy of LWD density predictions.

3. Minimum Absolute Percent Relative Error (MinErr):

$$E_{\min} = \min_{i+1}^{n} |E_i|$$

4. Maximum Absolute Percent Relative Error (MaxErr):

$$E_{\max} = \max_{i+1}^{n} |E_i|$$

5. Root Mean Square Error (RMSE):

It is a measure of data dispersion around zero deviation. Mathematically:

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n} E_i^2\right]^{0.5}$$

6. Standard Deviation (STD):

It is a measure of dispersion. Mathematically:

$$STD = \sqrt{\left\{\left(\frac{1}{m-n-1}\right)\sum_{i=1}^{m}\left[\left(\frac{\rho_m - \rho_p}{\rho_m}\right)\times 100\right]^2\right\}}$$

where (m-n-1) is the degree of freedom in multiple regression. As the values of standard deviation gets lower, it indicates that the data are less scatter.

7. The Correlation Coefficient (R):

It is a measure of the degree of success in reducing the standard deviation by regression analysis. Mathematically:

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}\left[\left(\rho_m - \rho_p\right)_i\right]^2}{\sum_{i=1}^{n}\left[\left(\rho_m - \overline{\Delta\rho}\right)_i\right]^2}}$$

Where

$$\overline{\Delta\rho} = \frac{1}{n}\sum_{i=1}^{n}\left[\Delta\rho_m\right]_i$$

'R' values range between 0 and 1. The closer the value to 1, it represents perfect correlation. On the other hand, 0 values indicate no correlation among the independent variables.

VITAE

- Joined Saudi Aramco's College Degree Program for Non-Employees (CDPNE) in 2001.
- Sponsored by Saudi Aramco to study Bachelor Degree (BS) in Petroleum Engineering at King Fahd University of Petroleum and Minerals (KFUPM).
- Graduated from KFUPM as a Petroleum Engineer with honor in June 2006.
- Back to Saudi Aramco and worked as a petrophysicist in the Reservoir Description Division (RDD). Most of the experience acquired was concentrated on formation evaluation of mature and newly developed reservoirs.
- At the beginning of 2008, joined Reservoir Management Division (RMD) for a one-year rotational assignment as part of the Professional Development Program (PDP).
- Main tasks include:
    - Working closely with geologists and simulation engineers to plan and initiate new wells and sidetrack targeting areas for development and depletion.
    - Assessment of existing wells performance in mature reservoirs by utilizing all available data (Including pressure build-up tests, production logs, production history, Carbon Oxygen and resistivity saturation monitoring logs) and explore optimum ways to improve wells performance.
    - Estimate OOWC and made recommendations for new drilled wells locations based on the established OOWC.
- While working with Saudi Aramco, joined KFUPM Master Degree Program as a part time student.
- A member in the society of petroleum engineer (SPE) since 2003.
- Participated in many social activities.